# Indoor Positioning for Evaluating an Information System Used in a Hospital Environment

Master's thesis in Computer Science

Markus Liljebäck, 36637

Supervisors: Johan Lilius

Mats Neovius

Åbo Akademi University

Faculty of Science and Engineering

5.9.2018

# Abstract

This thesis provides an overview of the field of indoor positioning, including technologies, algorithms and methods used in the field. A case study focused on the analysis of tracking data has been performed for this thesis as well. The objective of the case study is to test methods for evaluating an information system used by medical personnel through the analysis of tracking data gathered in a hospital environment. For this, three different models of the personnel's mobility patterns are created for the time periods before and after the system's implementation, and are used to find a difference between these periods. The created models are Markov chains, average weeks of visit counts for each room and average visit durations for each room. These models are shown to uncover differences in the patterns which exist in various aspects of the data. The possibilities for using these results in an expert analysis of the system are examined.

**Keywords:** Indoor positioning, tracking data, mobility patterns, information system evaluation

# Preface

The case study performed for this thesis is part of a project performed by the Embedded Systems Laboratory at Åbo Akademi University in cooperation with TYKS (Turku University Hospital). I would like to thank Sanna Salanterä for her efforts in arranging the financing for the project and the work performed in this thesis. I would also like to thank Laura-Maria Peltonen for her assistance in working with the hospital data set, as well as my supervisors Johan Lilius and Mats Neovius for their support during the writing of the thesis. Other researchers who have been involved in the technological part of the data collection process of this project are Valentin Soloviev and Stavros Ntentos.

# Table of contents

# 1 Introduction

## 1.1 Goal of the thesis

The goal of this thesis is to give a broad overview of the field of indoor positioning and to perform a case study where indoor positioning data is analyzed. The overview includes the algorithms and methods used within the field, as well as the non-technological aspects to consider when designing an indoor positioning system. Mathematical descriptions of the methods and algorithms most relevant to the field of indoor positioning and to this thesis will also be given. The case study uses people-tracking data gathered in a hospital environment, and various methods for analyzing this type of data will be evaluated.

## 1.2 Case study

### 1.2.1 Problem description

The goal of the case study is to test methods for analyzing tracking data gathered on the movements of medical personnel, with the objective to evaluate a new information system which has been taken into use. The information system under evaluation is accessed through a mobile device (phone) and is intended to increase the working efficiency of its users. This efficiency has not been rigidly defined for this study. Rather, the goal is to evaluate various methods of analysis through which it would be possible to quantify the benefit gained from using the tool. An ideal result would be a clear value, e.g. a percentage describing how much less the medical personnel had to move around while using the tool. The different methods will be evaluated based on the usefulness of the results gained from them.

The data used for this study has already been collected, and the collection process is not a part of this thesis. The focus will be on the methods used to analyze the data, though the experiment setup will be presented and evaluated to some extent as well. The data used in this case study comes from two different studies with a similar setup and format for the data. The data has been collected in three different hospitals, with collection periods before and after the system's implementation. The data has been gathered by placing beacons inside the hospital, which broadcast their presence using Bluetooth technology. The phones then detect these beacons and store the properties of the received signal. The collected data is in a raw format, meaning cleaning and preprocessing will have to be performed on it prior to analysis. The data collection setup, the properties of the data, and the performed preprocessing will be covered in greater detail in section 4.

### 1.2.2 Approach

The initial steps are focused on gaining information of the data set and modifying it into a format fit for analysis. This is done through first examining the contents of the data set to gain an overview of how much data each different collection period and device has. The data is examined through various statistics and experimental visualizations. Based on this overview, what data is considered to be erratic is defined and the data set is pruned to remove this data. The data will then be split into "on-call" time and "normal" time according to the timestamps of the readings, based on received domain knowledge for the hospital environment. Based on what information is available, the methods deemed best at making use of this information are chosen.

The next phase consists of applying the methods which have been chosen to find a difference between the periods prior to the system's implementation and the periods after its implementation. Three different approaches are examined. The first approach is to create Markov chain models of the areas and to analyze the people flow in them to find a difference between the periods before and after the system implementation. The second approach which is used is to create an average week of the amount of visits each room in the hospitals receives, and to compare the weeks before and after the system implementation. The final approach is to make use of the time information in the data by calculating average visit durations to each of the sites' rooms.

Finally, the results from using the different methods will be evaluated. The patterns which are found will be examined, taking the experiment setup and the amount of data which has been collected into account. After analyzing the found patterns and their implications, it is determined to what extent it is possible to draw conclusions about the system's efficiency based on the findings. This includes what other variables affecting the movement patterns would need to be ruled out, and which types of questions can be answered based on this type of results. Possible problem formulations for evaluating the efficiency of the system under evaluation and for other similar cases based on these questions will be proposed.

## 1.3 Limitation of scope

While a comprehensive overview of the technologies and algorithms used within indoor positioning is given in this thesis, it is not intended as a survey of the field. Technologies and algorithms will be presented from a general perspective, and a survey of specific positioning systems which exist is not performed. However, real world examples will in many cases be provided for the concepts which are presented. The fields of outdoor and indoor positioning are closely related, but a comprehensive overview of outdoor positioning systems will not be given in this thesis. However, as indoor positioning can in many ways be seen as an extension of outdoor positioning, the connections between them will be covered where they are relevant.

### 1.4 Structure and notation

The structure of this thesis is as follows: first, indoor positioning systems will be presented from a technical point of view, with details related to the design of the systems as the focus. This includes the choice of technology, representation of position, algorithms used, as well as other aspects to consider when designing this type of systems. The next part focuses on the theory of the methods and algorithms used within the field and for the performed case study. Then, the case study performed for this thesis will be presented, including an overview of the positioning system which has been used to gather the data, which methods have been used to approach the problem, and a description of how these methods were implemented to perform the analysis. The results and their implications will be discussed, and the used methods will be evaluated based on this. The concluding chapter will summarize what has been done in the thesis and present future prospects for performing this type of analyses.

The section focusing on the theory of the methods used in the thesis will contain mathematical descriptions of the approaches used in the thesis. The mathematical notation used is kept consistent throughout the thesis, and is as follows: Lower case letters are used to denote scalar values, with $i$, $n$ and $m$ always representing integers and $r$, $s$ and $t$ always representing real values. Upper case letters are used to denote matrices, sets and functions. Lower case Greek letters will be used to denote angles. A vector is denoted by a lower case letter with an arrow on top. The element at position $(x, y)$ in a matrix $P$ will be denoted $P(x, y)$.

## 2 Indoor positioning systems

Indoor positioning systems are systems which are used to collect data on the position and movement of people or other entities in indoor space. The field of indoor positioning is centered around designing these systems and utilizing the gathered data, and has various areas of research such as indoor tracking and indoor navigation. It is closely related to the field of outdoor positioning and follows the same general principles, but the collection technologies and utilized methods are different. When analyzing the data, further differences emerge in how one may choose to model the area the data has been collected from and what information is deemed relevant to include in the analysis. Common uses for indoor positioning data include location detection in mobile robotics, human navigation systems or, as in the case study performed for this thesis, tracking the movements of people. [1][2]

A common technology used for outdoor positioning is the Global Positioning System (GPS), but the usability of GPS is greatly limited in indoor environments due to the satellite signals being weakened by the buildings, thereby greatly reducing its accuracy. In most cases it is of interest to know the position of the entities on a room-level accuracy, which limits how large the error margin is allowed to be. Multiple different types of technologies have been developed for indoor positioning, with the most popular ones utilizing widely available radio frequency (RF)-based technologies such as wireless local area network (WLAN, also known as Wi-Fi). In the following subsections, an overview of the different ways positioning systems are categorized will be provided, followed by an overview of the technologies and algorithms used when developing positioning systems. The concluding subsection summarizes the aspects related to privacy which need to be considered when developing a positioning system. [1]

## 2.1 Overview

### 2.1.1 System types

Several different ways to categorize indoor positioning systems exist. These include categorizing them according to system topology, the medium used for positioning and the technologies used in the system. The topology of the system being designed is chosen according to its intended application. The topology is determined by which parts of the system are stationary and which are mobile, which parts have a known location, and what frame of reference they operate in. The medium used for positioning refers to what types of signals and sensors are used to identify the position of an entity. This is related to the technologies used in the system, but there exist several different technologies utilizing each medium. Both of the latter forms of categorization are diffuse, as systems may utilize several different technologies for positioning and the exact technologies used in proprietary systems may not be known. The following sections will present categorization according to system topology and transfer media, while the technologies used for indoor positioning are presented in greater detail in section 2.2. [1][3]

Liu et al. [1] categorize indoor positioning systems into four different types of system topologies, based on an earlier categorization of GSM-based outdoor positioning systems by Drane et al. [4]. This categorization is based on whether the signal transmitters and the measuring units (receivers) are stationary or mobile, and where the positioning computations are performed. The most common of the four is the *remote positioning system*, in which a mobile signal transmitter contacts stationary measuring units and then sends the data to a central system for processing. The second topology is the *self-positioning system*. In this type of system, the measuring units are mobile and the signal transmitter is stationary with a known location. The measuring units are capable of determining their own position based on the received signals. The third and fourth topology are variants of the self-positioning system, labeled as "indirect" versions of the first two, with the difference being the location where the positioning data is processed. Accordingly, the third topology is called the *indirect remote positioning system*, with the difference to the the self-positioning system being that the measured positions are processed remotely. The final system topology is the *indirect self-positioning system*, which is another variant of the self-positioning system, in which the mobile measuring units share their positioning data among each other. Generally speaking, remote positioning systems are more common within tracking applications, while self-positioning systems are used within navigation, e.g. for mobile robotics.

Another way of categorizing positioning systems is by the medium used for obtaining the position of an entity. Gu et al. [3] identify six different categories of this type for indoor positioning systems. These are: radio waves, visual light, infrared light, ultrasound, audible sound and magnetic fields. Radio waves are the most common transfer media used in both indoor and outdoor positioning, and there exists a large variety of technologies utilizing them. Infrared light is a medium which requires visual contact between the sensor and tracked device, and which can be disrupted by strong light sources. Visual light is similar to using infrared light when simple light sensors are used, but this category also encompasses camera-based systems which use image recognition rather than simply using light as a signal for detecting tracked entities. Systems using magnetic fields use either a self-generated magnetic field or the Earth's magnetic field to detect the location of its tracked entities. All of these media have their advantages and disadvantages, which should be taken into account when designing a positioning system. An example of the practical implications that the properties of different signal types have for the design of the system are presented in illustration 1, where a comparison of signals requiring line of sight and those which do not is presented.

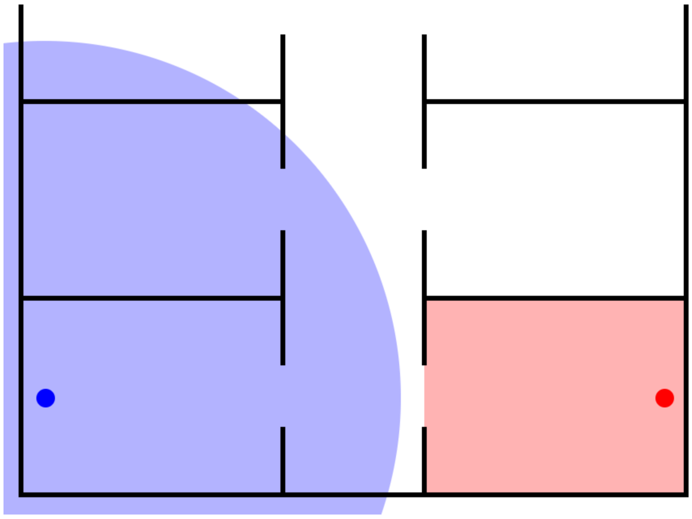

**Illustration 1:** An example of how the signal range differs between arbitrary signals with different line-of-sight requirements. The blue area represents the range of a transmitted signal which does not require line of sight to the receiver (e.g. radio waves) and the red area represents the range of a signal which does (e.g. light).

### 2.1.2 Areas of application

The different areas of application where positioning systems are used include tracking systems, location based services and navigation systems. Tracking systems are used to track people, equipment or other entities of interest, either for commercial or research purposes. Location based services are services which take the user's geographical location into account to provide additional information or entertainment. Navigation systems are used either as a part of a location based service, for automation in e.g. robotics or for guiding emergency personnel to their target location. The remainder of this section will give descriptions of these different areas of application. [1][5]

Tracking systems is one of the most well-researched areas of application for indoor positioning systems, as all positioning systems are based on tracking the location of various entities even if the end application may be different. When used to track people, it is often to analyze their behavior or to analyze the people flow aspects of the area the tracking is performed in. Other uses for tracking systems include tracking of a company's stock in a warehouse or the tracking of expensive equipment e.g. in hospitals. The main users of tracking systems are researchers and companies. Tracking systems are rarely provided directly to end users, but rather used to enable context-aware services or other location based services. [1][6]

Location based services are, according to Basiri et al. [5], used actively by 74% of all who own a smart mobile device, making it a major area of application for positioning systems. However, the majority of these services rely solely on outdoor positioning, which degrades the quality of the services in indoor environments. The use of indoor positioning systems for location based services is an area being developed, with e.g. hybrid infrastructures which combine indoor and outdoor positioning being an area of research. Context aware services are a type of location based services, in which a positioning system is used to provide additional value to the user of the service, but which do not directly rely on the position. As an example, a service providing information about products in a store can determine the user's interest towards a specific product through their proximity to the shelf where the product is, and provide additional information without requiring input from the user. [7]

Navigation systems refer to systems where wayfinding is provided as a location based service for consumers, but also systems which are designed to guide people through a building or to automate navigation. Navigation systems often rely on data on various levels of abstraction, using both positional data and information about the environment, such as landmarks. Both human navigation systems and navigation used in robotics utilize this type of information. Navigation systems which assist with navigation in a known environment is a well developed area, but navigation systems which allow precise navigation through unknown environments, especially indoors, is a field actively being researched. Such a system would have many important applications, with guiding rescue teams to people in a burning building being an example. For robotics, such a system would have similar uses within rescue operations or when navigating environments which are too hazardous for humans to navigate. [2][8]

### 2.1.3 Representing position

Positioning data can be represented in many different forms, with the most central features differentiating them being whether the representation is for a physical location or a symbolic location, and whether it is an absolute position or if it is relative to some other entity. For physical location, the positions of the entities are represented as coordinates on some type of map, whereas for symbolic location their positions are represented in a natural-language way, e.g. using the names of the rooms they are located in. For absolute positioning, all the entities use the same frame of reference, while for relative positioning the locations of the entities are expressed in relation to each other or to other known objects. [1]

Choosing how to represent the position of entities is done according to the needs of how the data is going to be used, and is one of the first steps when designing a positioning system, as it dictates what technologies, algorithms and models may be used. The goal with the representation is for it to be as exact as possible, both in regards to time and position. Since all positioning information obtained from positioning systems are estimates based on sensor readings, a margin of error will always be present. Therefore, an acceptable margin of error should be defined early on in the system design process, and the technologies and positional representation chosen according to this. How positioning data is represented when it is gathered can differ greatly from how it is represented during analysis, as the data is usually fitted to some model which simplifies and streamlines the data. Modeling of indoor space will be presented in section 3.1. In the remainder of this section, the various categories of representations of positioning data will be presented in greater detail. [9]

Physical position refers to coordinates in either two or three dimensions, and symbolic position refers to information on a higher level of abstraction. Physical position is commonly obtained through methods such as triangulation, with parameters estimated based on sensor readings, while obtaining symbolic location can be regarded as a classification problem. When determining the symbolic location of an entity, it can be done by first obtaining its physical location and then classifying it into the corresponding symbolic location. However, the accuracy of physical position representations often suffers from the unpredictability of indoor environments, depending on the technology used, meaning the position will always have some margin of error. This error will then propagate to the symbolic representation, as many border cases will be misclassified due to the margin of error the physical representations have. Therefore, it may provide better results to directly classify the entity's symbolic location based on the available sensor readings that the physical location estimates would be based on. Representing position symbolically is closely related to semantic models, which utilize this type of positioning information. The choice of a physical or symbolic data representation does not have to be absolute. Depending on the system used, it may be possible to gather the sensor readings and use them for obtaining both a symbolic and physical representation of the data. However, taking the desired data representation into consideration already in the system design phase allows the optimization of the system for the target data representation. As an example, if an accurate room-level representation is desired, partitioning sensors at the doorways can be added as a part of the system design. [1][10]

Whether positioning data is absolute or relative is defined according to whether the tracked entities use the same frame of reference or not. In absolute positioning each object uses the same frame of reference, e.g. a map where the data consists of coordinates or room information, while for relative positioning each entity has its own frame of reference. Relative positioning data may consist of information such as the distance between the entities themselves or the distance between the entity and a specific landmark. Cases where the data for all entities consists of distance to the same landmark or set of landmarks (e.g. mobile base stations), they can be seen as using the same frame of reference. Using absolute positioning is common for both real-time applications and for positioning data intended for analysis, while relative positioning is mainly applied in real-time applications. Examples of areas where relative positioning is applied are within human navigation systems and spatial coordination between robots. [2][8]

## 2.2 Technologies

One of the first choices to make when designing a positioning system is generally which technology to utilize. This choice is dictated by designated cost, accuracy and performance constraints. The chosen technology determines whether there will be an existing infrastructure to utilize for the system's implementation, e.g. routers for a system using WLAN. Designing a new system for the sake of full control of all factors may be desirable if the case being studied has high accuracy requirements or other performance constraints. However, building a custom infrastructure makes the system more costly and difficult to deploy in new locations, limiting its scalability. Using existing infrastructure, including routers, phones, or similar to perform the data gathering is often preferable when performing data collection on a large scale. The most commonly used technologies for indoor positioning are the RF-based ones, but there also exist systems which utilize various outdoor positioning technologies as well as optical systems, acoustic systems or those combining multiple different technologies. In the following sections, more detailed explanations will be given for the various categories of technologies commonly used for indoor positioning. [1]

### 2.2.1 Outdoor positioning technologies

Outdoor positioning systems have been studied and developed for a longer time than indoor positioning systems, and most of them are RF-based. The same technologies used for outdoor positioning systems generally cannot be used indoors due to challenges which are not present in outdoor environments, such as the structural elements of the buildings weakening the signals and the signal multipath issues caused by the greater amount of obstacles. The accuracy requirements of indoor positioning systems are also in most cases greater than that of outdoor positioning systems. The most common category of technologies used for outdoor positioning is *global navigation satellite systems* (GNSS), of which the US government-owned GPS is the most commonly known. It is the positioning system which has been in development for the longest time, and has become the de-facto standard among outdoor positioning systems. It consists of 24 satellites orbiting Earth in a way that at least four satellites are visible from any given location. Examples of other GNSS systems include the Russian GLONASS and the European Galileo systems. There also exist cellular outdoor positioning systems, which utilize the base stations of the cellular network for obtaining the positions of mobile devices connected to the network. [1][11][12]

The accuracy which can be achieved by positioning systems relying on GPS is 1-5 meters in outdoor environments, but they are generally not applicable in indoor environments due to how they depend on satellite coverage. Solutions for utilizing GNSS in indoor environments include the use of stations which mimic GNSS signals or to use high-sensitivity GNSS receivers. Both are, however, very expensive compared to standard indoor positioning technologies, with the price ranging in hundreds of Euro per receiver or station. Actual GNSS signals may also interfere with these systems, reducing their accuracy. The provided accuracy of these types of systems is about 5 meters, but most systems based on technologies developed specifically for indoor environments are able to provide more accurate positioning than this. The cellular systems used in outdoor positioning have little usability in indoor environments due to their accuracy being 50-200 meters, which is lower than that of standard GNSS systems indoors. The only case in which the accuracy of this type of systems would be better is if the building was surrounded by base stations. [1][5][12]

### 2.2.2 Radio frequency (RF)-based systems

RF-based indoor positioning systems use the knowledge of how radio waves propagate to localize the tracked entities. The most common RF-based technologies are Bluetooth, WLAN and radio frequency identification (RFID). Other RF-based positioning technologies include those using ultra wideband (UWB) and ultra high frequency (UHF) radio signals. The differences between these technologies include the frequency of the signals as well as the standards and protocols used by each technology. The remainder of this section will present the most common RF-based technologies in more detail. [1][7]

Bluetooth and WLAN are both technologies used for short-range wireless communication. These technologies are common choices when designing general-purpose people tracking systems, as they utilize features which are present in the smartphones carried by most people. Both are RF-based technologies operating on different bandwidths. Bluetooth features a lower gross bit rate and a shorter range, 10-15 meters compared to WLAN's 50-100 meters. WLAN is the most studied technology for indoor positioning systems and also the most commonly used one, while Bluetooth is more recent due to how certain relevant features were absent in the early Bluetooth standards. Most indoor environments nowadays have an existing WLAN infrastructure, while Bluetooth beacons must be deployed separately. The WLAN routers are most likely not placed with an indoor positioning system in mind, however, which may reduce the accuracy of a system built directly upon this infrastructure. The power consumption of these technologies also affects how they can be used. Bluetooth consumes significantly less power than WLAN, and Bluetooth beacons are often battery-driven with a battery life of 1-2 years, while WLAN routers usually need to be connected to a power supply to function. When weighing the two technologies against one another, Bluetooth can be seen as a lighter alternative to WLAN, with lower power consumption and cost being the main benefits. However, WLAN does not require the sensors to be placed as densely as Bluetooth, due to its greater range. When power consumption is important, such as with mobile devices, Bluetooth is often the preferred technology. [1][10][13]

When RFID is used in tracking systems, it is usually done by placing RFID tags in the area to be surveyed and having the entity to be tracked carry a reader which detects these tags. RFID tags can either be active or passive, with passive RFID tags not requiring any power supply to function. The usability of RFID is greatly reduced from requiring the entity being tracked to carry a reader, as well as the low range of passive RFID tags (1-2 meters). Active RFID tags can have a range of over 10 meters. RFID is commonly used alongside other technologies to partition an area, e.g. when the exact room a person is in is important. The RFID tags are then placed on both sides of a door, and the order in which the tags detect the entity gives whether the entity is entering or exiting the room. Tracking systems which rely solely on RFID are generally only suited for dense environments. Navigation systems based on RFID are created by placing tags in the area, which the system's user then reads and obtains additional information from when navigating the area. RFID is also a popular technology when tracking objects, e.g. for inventory management or expensive equipment in places such as hospitals. [1][14]

### 2.2.3 Optical systems

Optical positioning systems encompass all the systems which utilize light to locate the tracked entities. This includes technologies like infrared (IR) light, lasers, light emitting diode (LED) lights or cameras. Light shares many properties with radio waves, with the key practical difference for positioning being the requirement of line of sight between the tracked entity and the measuring unit. Generally, optical systems are more expensive than other technologies used for indoor positioning, but provide excellent accuracy with the error margins ranging from a few micrometers to a few centimeters. [15]

Systems using sensors for visual light or IR light utilize knowledge of how these signals propagate to pinpoint the location of entities in an environment, similarly to systems based on radio waves. Depending on the system design, the tracked entities may be the ones carrying the light-emitting signal transmitters, or they may be placed in the environment with the subjects carrying sensors instead. The use of existing infrastructure is possible in systems using visual light by making the lights of an area modulate their emitted light in a way not distinguishable by humans in order to make them uniquely identifiable, thereby making them possible signal transmitters in a positioning system. The advantages IR light has over visual light is that there is less interference from ambient light, and that the system is less noticeable in case existing infrastructure is not used. Lasers are used for positioning in two ways: range imaging and partitioning. A positioning system proposed by Gőzse in [16] is an example of how an optical system based on LEDs may work. It utilizes a device based on the concept of a pinhole camera to track the angle in which the entities marked with LEDs are located. [15]

Optical systems which use cameras work differently from the systems utilizing simpler light-sensors to detect the tracked entities, as they utilize image processing algorithms to identify the entities and pinpoint their location. This approach is related to computer vision, and requires significantly larger quantities of processing power to perform than other positioning calculations, making these systems a fairly recent development within the field of indoor positioning. There exist both systems where the tracked entity carries a camera and those where cameras are mounted in the area of interest, with the former being mainly used for navigation systems and the latter mainly being used for tracking systems. There exist systems which work both with and without tags located in the environment or on the tracked entities, with purpose of these tags being to help the system perceive depth and locate tracked entities. Passive tags are tags which reflect ambient light and active tags emit their own light. These tags are detected in the image processing algorithms, and are used to obtain a location of the entities for a tracking system or the location of the entity carrying the camera in a navigation system. In tagless systems, other characteristics are used to tell apart the entities of interest, e.g. people, from the rest of the environment. Tagless systems require more complex approaches to perceive scale and depth than systems using tags. In the case of systems using stationary cameras, the data from multiple cameras is required for this, while a mobile camera can use an approach called synthetic stereo vision to perform these estimates. Depth can also be obtained using additional sensors, such as range imaging cameras or laser scanners. [7][15][16]

### 2.2.4 Acoustic systems

Acoustic positioning systems are systems which utilize knowledge of how waves of audible sound or ultrasound propagate to pinpoint the locations of tracked entities. Technologies relying on the same principles have been used in navigation for a long time, most notably sonar systems for marine navigation. Acoustic systems are laid out in a similar manner to RF and optical systems, with signal transmitters and receivers using properties such as time of flight or received signal strength to determine the location of a tracked entity. Sound waves have different properties from radio waves, however. They travel slower, and do not penetrate walls and other objects as well as radio waves do. The property of not being able to penetrate walls well is shared with signals of visual or IR light, but line of sight between the emitter and receiver is not necessary to the same extent as with light. [3]

Acoustic systems can be built using nodes specifically designed for the task, but the use of existing infrastructure is also possible. As an example of an audible-sound system using existing infrastructure, speakers playing music in a public location can be made to modulate their sound in unique ways, creating a network of identifiable signal transmitters which can be used by a mobile receiver to calculate its position, as the speakers' locations are known. The nodes in an acoustic system need to stay synchronized to provide proper results, and this synchronization cannot be performed using the sound signals themselves. In wired solutions the synchronization can be easily performed through the connecting wires, but in wireless solutions the nodes are often given capabilities for radio communication to perform the synchronization between each other. Acoustic systems cost less than optical systems, but can provide similar levels of accuracy, with the error margin being around a few centimeters. The disadvantage of these systems is that they consume more power than RF-based and non-camera based optical systems, making them less practical for designs where the signal transmitter lacks access to a power source. [7][11][17]

### 2.2.5 Other technologies

Other positioning technologies include inertial positioning systems, magnetic positioning systems, and numerous proprietary and hybrid technologies. Inertial positioning systems are those which estimate position from readings of accelerometers, gyroscopes or pedometers. The weakness in this form of positioning is that these systems lack a frame of reference and errors will accumulate over time. Therefore, they are almost always used in combination with other technologies to enhance the readings obtained from other sensors. Magnetic positioning systems use magnetometers as sensors, and include those generating their own magnetic fields and those which use the Earth's magnetic field for positioning. Signal transmitters in systems generating their own magnetic field use direct current (DC) magnetic pulses which are detected by the sensors. These systems can provide precise tracking in 3D space, with an error margin of less than a centimeter, allowing for applications such as precise body movement tracking. The disadvantages of this type of systems is the short range of the magnetic fields (~3 meters), and that the signal transmitters are expensive and consume large amounts of power. Systems using the Earth's magnetic field commonly use a method called ambient magnetic fingerprinting, where the readings from the sensors are connected to a location based on a signature or "fingerprint" assigned to this location. This works well indoors, as the structural elements of buildings (e.g. steel structures) cause fluctuations in the Earth's magnetic field. Fingerprinting is a commonly used method for several technologies within indoor positioning, and will be covered in greater detail in section 2.3. [3][7][18]

The combining several of the previously mentioned technologies is common in proprietary systems, and their exact functionality is often not revealed. Combining different types of data representing the same information from several different sources is known as *sensor fusion*. An example of a standard application for sensor fusion within indoor positioning is to use RF positioning as an alternative positioning method in acoustic systems, since wireless signal transmitters in these systems are often equipped with RF capabilities. Another example is the use of sensors which cannot alone be used for positioning, such as digital compasses, to enhance the predictions which can be made from the readings. Multiple technologies can be used to perform different tasks in the systems as well. As an example, a camera-based system could be used to count the people entering and exiting an area, RFID sensors could be used to accurately partition the area and a third technology could be used for the actual physical positioning calculations. A major area of development is the combining of outdoor and indoor positioning technologies to create hybrid infrastructures where the two types of positioning could be seamlessly integrated. [1][11][14][19]

## 2.3 Algorithms

A wide range of algorithms focused around making position estimates based on sensor readings is used within the field of indoor positioning. The following subsections will present several of the algorithms and methods used within the field. The first group which is presented consists of probabilistic and machine learning (ML) methods. Indoor environments are challenging locations to perform positioning in due to issues like low line of sight, many reflective surfaces, and many mobile entities in the area, and these methods have been shown to be useful in mitigating the errors caused by these challenges. The next group consists of methods utilizing knowledge of how different types of signals propagate in order to make distance or angle estimates for use in geometric positioning methods. These are commonly used, as signal-based systems are the most extensively developed positioning systems. They are applicable to most signal-based systems, including RF-based systems, optical systems and acoustic systems, despite the signals having different physical properties. The next approach is fingerprinting, which is an approach that has been shown to provide better results than methods based on signal propagation in most generic cases, while requiring more effort to set up and maintain. Finally, other algorithms which are more technology-dependent are presented. These include computer vision algorithms for camera-based systems and dead reckoning for inertial positioning systems. [1][11][20]

### 2.3.1 Probabilistic and machine learning (ML) methods

Probabilistic and ML methods are used both to make positioning estimates directly, as well as in conjunction with other methods to counteract the problems caused by the challenges in indoor environments. Because sensor readings cannot be used directly in positioning calculations, making estimates based on these readings is necessary. The challenges present in indoor environments cause deviations in the quality of these readings, which then propagate to the final result. In order to mitigate the effects of this issue, the use of probabilistic and ML methods is common. The main area of application for these methods is for fingerprinting, though they have several other applications as well, e.g. reducing the negative effects of signal noise. Several of these approaches have a high mathematical complexity, and covering their exact functionality is outside the scope of this thesis. In this section they will be covered from a general perspective, while how they are applied for specific positioning approaches will be presented in the respective section for each approach. [1]

Probabilistic methods commonly used within indoor positioning include Bayes' formula, kernel methods, and Markov chains. Bayes' formula is a method from probability theory, used to calculate the probability of an outcome based on prior outcomes. Similarly to the ML methods, it can work with feature vectors which represent events, which in turn are linked to certain outcomes. Kernel methods are often used to alleviate the decrease in accuracy that the spatial or temporal discretization used in other probabilistic methods may cause. The probabilistic, kernel-based mobility prediction framework proposed in [21] is an example of how kernel methods may be used within positioning. Markov chains can be used as probabilistic transitional models of the area, which in turn can be used to improve the positioning estimates by giving the possible locations of the entity a weight based on their previous location. One downside of probabilistic methods is that many of them rely on properties such as the variables following a Gaussian distribution and independence between the variables. Notably, the fluctuations of the RSS in RF-based systems do not follow a Gaussian distribution, but many approaches make such an assumption nonetheless. [1][22]

ML approaches commonly used within indoor positioning include k-nearest neighbors (kNN), naive Bayes (NB), artificial neural networks (ANN) and support vector machines (SVM). ML methods can be divided into two categories: supervised and unsupervised methods. Supervised methods need to be "trained" using an example data set, while unsupervised methods do not. Another form of categorization is according to the type of problem they solve, and in the case of indoor positioning the most important ones are classification and regression. Classification categorizes provided input values into discrete classes, while regression returns continuous values. Most ML algorithms take an $n$-dimensional feature vector as input, where the features are numerical representations of the variables being examined. When training an ML algorithm, each feature vector is associated with a discrete or real value depending on if the algorithm is used for classification or for regression, respectively. Many of these ML approaches exploit the geometrical properties of the feature vectors, i.e. that they represent points in $n$-dimensional space, in order to perform classification or regression. The fact that the vectors are of equal length and can be arranged into a matrix is also used extensively. In indoor positioning, these features can e.g. be the strength of the currently heard signal from each beacon on the venue, with $n$ being the number of beacons present. [1][23]

### 2.3.2 Methods based on signal propagation

Positioning methods based on the propagation of signals are used for several different technologies, including RF-based technologies, optical technologies and acoustic technologies. Though these signals have different physical properties, how they propagate is well known and the same parameters describing their characteristics can be obtained for them. These parameters are: received signal strength (RSS), time of arrival (ToA), time of flight (ToF), time difference of arrival (TDoA) and angle of arrival (AoA). ToF is sometimes called round-trip time of flight (RToF) as well. RSS is mainly used for RF-based systems, and expressed in terms of a received signal strength indicator (RSSI), which is standardized for this type of systems. The goal in methods based on signal propagation is to estimate the distance between the tracked entity and the base station in question. This distance is used to calculate the position of the entity using either a proximity-based approach or geometric methods such as triangulation or trilateration. While the geometric methods themselves provide exact results, the parameters used in the calculations are always estimates based on sensor readings, meaning the accuracy is dependent on the quality of these estimates. Mathematical descriptions of triangulation and trilateration will be given in section 3.2, while this section will be focused on the sensor readings used for making these estimates. [1]

The proximity-based approach is an approach for determining the position of entities where the position estimate is entirely based on the node which the entity appears to be closest to. This means that the reading from a single sensor is enough to perform the localization. Different methods for determining which entity is closest include simply checking the strength of the signal, and also by performing the same distance-estimation methods which are used in the geometric approaches. In outdoor positioning, the proximity-based approach has mainly been used for tracking mobile phones, with the closest base station being considered the approximate position of the tracked mobile phone. However, for indoor positioning this approach has a wider range of uses, with examples including positioning in dense environments, the triggering of context-aware services and determining a person's interest towards something (e.g a shelf in a store). Proximity algorithms are commonly used for obtaining symbolic location information of entities, as they have low accuracy compared to more advanced algorithms. The quality of the measurements gained by these algorithms is improved if the sensors are placed densely across the area where the system is deployed, and in these cases the use of low-range technologies such as RFID or IR sensors is ideal. A variation of this approach is relative proximity sensing, which is focused on estimating the distance between the mobile units rather than performing positioning. This is used e.g for automated navigation in robotics. [1][8][24]

Both trilateration and the proximity-based approaches use estimates made for the distance between the beacons and tracked entities. Trilateration requires the readings of at least three beacons for 2D estimates and four beacons for 3D estimates. Distance estimates are made using ToA, TDoA or ToF. Systems using ToA estimate distance based on a one-way transmission of the signal, made from stationary signal transmitters to a mobile measuring unit. The signal includes a timestamp, which is used to calculate the distance based on the known speed of the signal. The ToA approach requires both the signal transmitters and measuring units to be precisely synchronized. Systems using TDoA also use a one-way transmission, this time from the mobile entity to stationary measuring units, and work by examining the difference in the signal's arrival time at the different measuring units. ToF systems work using a similar principle, but the signal is first transmitted from the mobile signal transmitter to the measuring units and then back, and the estimate is performed at the signal transmitter. TDoA and ToF systems only require the stationary measurement units to be synchronized amongst themselves. A combination of these is usually used in order to improve the quality of the distance estimates. In RF-based systems, RSSI is often used to estimate the signal multipath which may have occurred due to obstructions, in order to improve the quality of the estimates. This is done using one of the previously covered probabilistic or ML methods. As an example of possible input for such a method is to take the latest readings from a transmitter to identify strong fluctuations or noise to determine possible multipath which may have occurred. Using RSSI by itself does not, however, provide sufficient information to be used for making position estimates. Most technologies used for RF-based systems follow rigid standards and have all these parameters available, while other types of systems are usually designed with a specific approach in mind from the start. [1][25]

Approaches based on triangulation utilize the signal's AoA parameter. To use triangulation, AoA estimates are required from two beacons for 2D positioning and from three beacons for 3D positioning. In RF-based systems, this approach is less common than using distance estimates, as the hardware used in these systems does not support AoA estimation as a standard. The radio receiver must have directional antennae or antenna arrays in order to perform these estimates. The accuracy of AoA estimates in RF-based systems is often less accurate than the distance estimates, but if using both simultaneously is a possibility, the results may complement one another. In optical systems, AoA is used to a much greater extent. Both camera-based systems and simpler photo diode-based systems use angle estimates for their positioning calculations. [13][15][16]

### 2.3.3 Fingerprinting

Fingerprinting, also known as scene analysis, is the method of directly estimating an entity's position based on the signal parameters, rather than estimating the parameters used in e.g. geometric calculations. This is done by mapping locations in the area where the system is deployed to characteristics of a received signal, which will be the "fingerprint" of that location. Fingerprinting can be formulated both as a classification problem and as a regression problem. As a classification problem, the result is either a symbolic location (e.g. a room) or a physical position from a discrete set of positions which have been used for training. When classification is used for physical positioning, the maximum possible accuracy is determined by how densely these positions have been sampled. As a regression problem, the result consists of coordinates in either two or three dimensions. Both probabilistic methods and supervised ML methods are used for the classification and regression approaches to fingerprinting. Simpler approaches exist as well, e.g. simply picking the closest match among the gathered data, but such approaches are easily outperformed by those using more intricate models, due to the fluctuations commonly present in indoor positioning data. [1][3][12]

The fingerprinting process includes an "offline" and "online" phase. The offline phase is the training phase. During this phase, the system has access to the actual positioning information, and uses it to create or modify the decision model to be used in the online phase. Both the probabilistic and ML methods take a signal vector as input. The size of this vector is always constant throughout both phases, and each value always represents the same property. A common type of signal vector is one where each value represents the signal strength of a transmitter on the venue, with each transmitter always being included regardless if they are heard or not. For several ML approaches, it is possible to include multiple properties per transmitter or to use differing types of transmitters, as long as the representation is kept constant. For probabilistic approaches, this is more difficult due to how many of them are based on one value representing one location, and the output being the probability for each of these locations being the closest one based on the respective values. [1]

All probabilistic and ML methods which are used for classification and regression can be used for fingerprinting. Probabilistic approaches often treat the positioning in fingerprinting as a classification problem. When using probabilistic methods to obtain physical positions, the classification step is often an intermediary step in obtaining a result similar to a regression algorithm would give. One method for obtaining an estimate consisting of continuous values for the coordinates is to calculate a weighted average of multiple possible discrete positions, where the probability of each of the respective positions is their weight. Probabilistic methods take a signal vector as input, and using a decision rule the most probable position is selected. For the probability calculations, common approaches include the use of Bayes' formula or kernel-based approaches. ML methods are used extensively for fingerprinting, with commonly used methods including the previously mentioned kNN, ANN and SVM algorithms. As input, these methods take a signal vector in the same format as the probabilistic approaches do. The system proposed in [12] is an example of fingerprinting using an ML method, where an SVM algorithm is used for obtaining the symbolic location of a tracked entity based on the available signal parameters. [1][10]

Due to sharp fluctuations which may occur in signal readings in indoor environments, the data may be smoothed prior to performing fingerprinting for better results. The goal of smoothing is to remove noise and sharp outliers based on prior and subsequent readings, while preserving important patterns in the data. If the data were to be portrayed graphically, the resulting graph would appear smoother after such a method is used. Smoothing methods are commonly used in conjunction with ML methods as well to create better predictive models, and some are integrated into the algorithms themselves. Examples of smoothing algorithms include Kalman filtering and particle filters. An example of an ML method with smoothing integrated is the smooth support vector machine, proposed in [26]. [7][27]

Generally, fingerprinting provides higher levels of accuracy than the methods based on signal propagation. However, fingerprinting always requires large amounts of training data, and the quality of this training data is what determines the accuracy of the positioning estimates. Gathering training data is a very time-consuming task, and may be difficult to do accurately in densely trafficked areas. When gathering training data, it needs to be done when the venue is in a state it is expected to be in when the system is active, as the people and other obstructions will have a major impact on the gathered location fingerprints. Another advantage signal propagation based methods have over fingerprinting is that they facilitate sensor fusion, as estimates of distance or angles can be used in the same method regardless of which sensor's readings the estimate is based on, and new sensors can be added later on. Fingerprinting, on the other hand, would have to be explicitly trained with combinations of different types of readings, which makes the adding of new sensors at a later stage of the system's implementation an exceedingly time-consuming task. The accuracy of fingerprinting also degrades over time due to how changes happen in the environment, e.g. obtaining new furniture for an office space may change the signal properties of the area. [10][20]

### 2.3.4 Other algorithms

Other noteworthy algorithms used for positioning include dead reckoning, image processing algorithms and algorithms for sensor fusion. Dead reckoning is a method of positioning where the position of a tracked entity is estimated based on a known initial position, and the speed and direction they have been moving according to since departing from the initial position. This type of positioning is used mainly in inertial positioning systems when no other sensors are available, and its most common area of application is within navigation systems. Due to the lack of other reference points than the starting position, errors accumulate over time when dead reckoning is used. Various solutions to improve the accuracy of this approach exist, including the use of filtering methods. [2][7]

Image processing is a broad field of its own, with a multitude of different algorithms being used to solve various problems. When creating a positioning system based on image processing, the used methods vary based on whether the cameras are static or whether they are carried by the tracked entities. In approaches with static cameras, the tracked entities need to be identified as separate entities consistently throughout the tracking process, and their positions need to be estimated based on the image data. Approaches to identify the tracked entities include feature tracking, contour tracking and ML approaches. Feature tracking uses tags or similar identifiers to tell apart entities, and contour tracking is used to e.g. tell apart people from other entities through their dynamically changing poses. ML approaches use manually annotated video data as training data to identify entities similar to the ones specified in this data. One downside of the ML approach is that manual video annotation is labor-intensive, though there exist systems which aim to decrease the workload through automation, e.g. the one proposed in [28]. Obtaining positioning information from images is called photogrammetry. In photogrammetry, geometrical methods such as triangulation are used for positioning with information extracted from the image. Information on distance and position of identified entities is obtained through having a specified reference plane, tags with known positions in the environment or depth information obtained through other means. Visual odometry is an approach used in systems where the tracked entity is carrying the camera, and works by performing estimates of position and orientation based on the gathered image data. It is a form of dead reckoning, with the direction and speed being extracted from the image sequence obtained from the camera. Similar approaches where tags with known locations are placed in the environment to provide additional information for the positioning estimates exist as well. [7][15][29]

Sensor fusion is used to increase accuracy, integrate different positioning systems or to provide an additional layer of certainty to safety-critical systems. An example of a safety-critical positioning system where sensor fusion is important is the navigation system of an autonomous vehicle. One approach to fusing the results of different positioning systems is to simply average their results, but there exist several more sophisticated approaches to make use of the information redundancy. Aspects to consider when implementing sensor fusion include the choice of fusion algorithm, fault detection, and collaboration between tracked entities. Fusion algorithms can be either centralized or decentralized, with the centralized approach having one algorithm perform the fusing of all the different sensors' readings, while a decentralized approach has several algorithms fuse individual readings, which then are combined. A centralized algorithm is often preferred. Common choices include Kalman filtering and its nonlinear variations, and ANNs. Fault detection is the process of identifying and isolating sensors which provide erroneous readings. This process has two steps, with the first one being the identifying of possible faults through the use of e.g. filter methods to compare actual readings to estimated readings. The second step is the binary decision process of whether the node is functioning correctly or not, commonly by comparing the errors to a threshold based on the signal variance. Collaboration between tracked entities can be used as an alternative method of positioning in case one entity loses its connection to the system. For this, the relative position to entities which are still able to calculate their position can be used for positioning until a connection is re-established. [1][7][30]

## 2.4 Privacy in positioning systems

The ever increasing capacity to collect and process data, as well as the trend towards increasing interplay between different types of systems pose challenges to the developers of positioning systems. The field dealing with the collecting, processing and analyzing of data on a grander scale than before has been coined "Big Data", and positioning systems are becoming a part of this development as well. The trend within positioning systems is a development towards hybrid infrastructures which combine outdoor and indoor positioning technologies. Such systems would drastically increase the amounts of data which could potentially be collected, as well as the accuracy of this data, providing the ones collecting it with an opportunity to gain a far more comprehensive view of the lifestyle of the subjects than positioning data from separate, enclosed areas would. The field of the Internet of Things (IoT) is focused on introducing network connectivity to devices traditionally not connected to the Internet in order to improve their usefulness, and many of these systems rely on positioning information in order to provide context-aware services. This makes positioning systems more prevalent in people's daily lives, often without their knowledge. [11][31]

These developments raise the privacy of people being tracked as a major concern, as well as safety risks resulting from the increased interconnectivity between systems. This poses challenges to legislators, providers of location based services, and the developers of positioning systems. Privacy is handled on several levels, starting with determining the extent at which it is ethically sound for companies to collect tracking data, share it, and use it to perform profiling. These restrictions need to be implemented on a legislative level, and then on a system level to ensure they are being followed. Safety-critical systems are more focused on security and correct functionality, but are part of this process nonetheless. The following sections will present the different ethical, legal and security aspects which need to be considered when designing positioning systems which provide the intended functionality while preserving the integrity of the data subjects.

### 2.4.1 Ethical aspects

The ethical aspects related to positioning systems are most prevalent in tracking systems, and include the privacy of the people being tracked, how the tracking data is used, and how the tracking may be performed without the knowledge or consent of those being tracked. However, all systems focused on the positioning of people store and process the same type of sensitive data. This section describes the ethical concerns present, while the following two sections describe how these concerns are being dealt with on a legislative and on a technological level, respectively. The privacy concerns of the users of location based services are centered around how their personal information is being collected, used and shared. There exist several definitions for what information can be considered personal information, but the common factor among them is that it is something which can be used to identify a person. Traditionally, anonymous positional information has not been considered personal information. However, it has been shown that as little as four anonymous spatiotemporal points of data are required to identify most individuals, leading to positional data becoming part of an increasing amount of definitions of personal data. [5][11][31]

In a survey conducted by Basiri et al. [5], it is shown that privacy is a major concern among users of location based services. Moreover, the users are more concerned for their privacy with regards to indoor positioning data than outdoor positioning data. It is also stated that a risk when introducing new location based services is the lack of understanding between the developers and users of the services, as the developers often underestimate the privacy concerns of their users, while the users often overestimate the threat to their privacy due to a lack of understanding of the issues present. The survey also shows that users desire different levels of protection depending on the type of service used. For services related to safety and security, high availability and quick response times are valued high while the protection of the users' privacy is not seen as important. For services related to entertainment or location based information retrieval, such as location based gaming or tourist information, privacy is only a medium concern. The services for which users are most concerned for their privacy are tracking, navigation and marketing services.

The challenges which the ethical aspects provide to developers of location based services include tight legal and security constraints, and also gaining the trust of the users of the service. Ethical aspects are also a major challenge when developing more generalized positioning systems which combine indoor and outdoor positioning. This is due to the sensitivity of tracking data increasing drastically when indoor positioning data is included, as it allows those who have access to the data to obtain a far more comprehensive view of the habits and lifestyle of the tracked subject than only outdoor positioning data would. Further challenges to the development of these systems stem from how these systems may depend on information which may be deemed to be infringing on someone's privacy or to be otherwise too sensitive to make publicly available. A map of a building which is private property or the map of a hospital are examples of this. [5][11]

### 2.4.2 Legal aspects

The legal aspects related to services using positioning data include data protection and certain standardization requirements. There exist differences between countries in regards to what information is considered personal information, how this type of information should be handled and in which cases the consent of the individual in question is needed. For systems which are to be deployed in a limited environment and only made to track specific individuals, e.g. for a research purpose, legal issues will most likely not be a limiting factor for the system's design. However, even though consent is obtained and the sensitivity of the data is low, most regulatory systems still require that data is handled according to good security practices. On the other hand, when developing commercial tracking systems or location based services, the laws in the intended deployment area will play a major role in the system's design. Aiming for an international market may require the system to follow several regulatory systems and the transfer of gathered data may also be limited by law. The remainder of this section will give a broad overview of the data protection and data transfer laws of the European Union and the United States, with a focus on issues related to positioning data.

In the European Union, the protection of individuals' personal data was until recently regulated by the Data Protection Directive (DPD) of 1995, but was replaced by the new General Data Protection Regulation (GDPR), effective as of 25. May 2018. The GDPR provides clearer and stricter regulations for the use of personal data, and for what data is considered personal. The GDPR states that the location data for a person is always considered personal data, and in order to lawfully gather this type of data the consent of the person in question is required. Prior to the GDPR, providing an opportunity to opt out from data collection was a sufficient form of consent, but the GDPR states that this consent must be expressly provided and affirmative. The consent must also be provided for the specific use the data is gathered for, meaning storing data for indefinite periods of time and using it whenever a need arises is no longer possible. Those who gather the data are also required to fulfill certain privacy and human rights requirements when handling the data, meaning they are obligated, among other things, to follow proper security procedures when processing the data. Which security procedures are considered adequate is determined by the estimated sensitivity of the data. The GDPR also contains a principle of *data minimization*, which states that only data relevant to the intended purpose should be collected. Minimization of collected data is one method to reduce the sensitivity of the data. [11][32]

In the United States, there are no general laws for data protection or for positioning data, but rather a set of laws regulating the financial activities of companies and usage of specific personal information, such as medical information. The Federal Trade Commission (FTC) Act suggests that companies should obtain the express consent of the person in question before using sensitive personal information, and "precise geographic location information" is included in this definition of sensitive personal information. However, obtaining consent is not a legal obligation. The Financial Services Modernization (Gramm-Leach-Bliley, GLB) Act states that companies must take adequate steps to protect gathered data using security practices such as encryption, and that they are obligated to inform the data subjects of their privacy practices. However, with the exception of certain health insurance information, data subjects do not have a right to know how information about them is used, and they do not have a right to demand that collected data about them is deleted. There exist certain states in the US, most notably California, with more specific laws regarding data protection and limitations to the uses of certain technologies commonly used for indoor positioning, e.g. RFID tags. [33]

Until 2015, data flow between the US and member states of the EU was regulated by the International Safe Harbor Privacy Principles. However, this agreement was invalidated by the European Court of Justice due to concerns regarding the surveillance programs of the National Security Agency (NSA) in the US. In 2016, the Safe Harbor agreement was replaced by the EU-US Privacy Shield, which provides an extension to the principles and obligations stated in the Safe Harbor agreement. Like its predecessor, Privacy Shield continues to allow personal data on EU citizens to be transferred to the US, but adds stricter requirements on the privacy policies of the companies storing and processing this data. One of these requirements is that the companies minimize the data they collect, and must be able to provide a legitimate interest for collecting and processing this data, according to the data minimization principles of the GDPR (and earlier, DPD). While Safe Harbor provided the users with the right to correct or delete incorrect information about them, it did not obligate companies and organizations to provide confirmation as to whether they have data stored about the subject in question. Privacy Shield addresses this, requiring companies and organizations to include the steps to take in order to do this in their privacy policy. Data transfer from the EU to other non-EU countries than the US is regulated according to whether the European Commission has deemed their data protection laws to be sufficient to comply with those of the EU. [34][35]

### 2.4.3 Security

The security aspects of positioning systems include the technologies and methods used to prevent unauthorized access to positioning data, protect against attacks targeted at the system itself and to minimize the negative effects in case of a security breach. Good security procedures are required both to protect the privacy of the users of the service and to ensure that safety-critical systems function as intended. Security is an important aspect in non-critical systems as well, as incorrect information in e.g. a company's stock tracking analytics could lead to loss of revenue. Security is often undervalued when designing location based services, either due to economic reasons or due to the threat not being perceived as significant. Software, hardware and system architecture are all factors which affect the security of a system. This section will the present security aspects to consider when developing a positioning system, which include standard data protection procedures which apply to all forms of sensitive data, as well as issues specific to this type of systems. [11][3]

Positioning systems require data to be transferred between the different parts of the system, often wirelessly, which makes unauthorized access to the data a risk. This risk can be minimized through having a system architecture which ensures a minimal amount of data transfer is needed and that the sensitivity of the data is low, and through ensuring the data transfer itself is performed securely. An example of a system architecture which reduces the sensitivity of transferred data is to have the tracked device calculate its own position based on a signal from a terminal, with minimal network communication needed. GNSS systems are an example of this. The sensitivity of the transmitted data is low, as the position of the device could not be determined by a third party even if the signal was intercepted. At the other end of the scale, a system where all positioning calculations are performed externally and transmitted to the user of the service, such as in a camera-based system, the sensitivity of the data is high. The main objectives in secure data transfer is to ensure the authenticity, integrity and confidentiality of the transferred data. Authenticity refers to being certain that the data truly has been sent by the advertised sender, and integrity refers to being certain that the data has not been modified in any way during transfer. Authenticity implies integrity, but not vice-versa. Confidentiality refers to being certain that no one but the intended recipient has possibility to access this data. The standard method used to ensure these properties in data transfer is the use of cryptography. [5][11]

Cryptography encompasses several methods for securing data which is stored or transferred. In positioning systems, the communication which needs to be secured is that between the signal transmitters, measuring units, and the unit where data is processed and stored. The most commonly used types of cryptographic functions include cryptographic hash functions, which are used to ensure data has not been altered in any way, secret key cryptography, in which a key known by both the sender and the recipient is used to encrypt and decrypt the data, and public key encryption, in which a publicly shared key is used for encryption while decryption is only possible by the recipient. The first of these only ensures the integrity of the data, while the latter two are used to provide secure data transfer. While these methods are widely used and have well-tested standard implementations, many indoor positioning systems have strict requirements for the power consumption and performance of the system, as they often rely on battery-driven, mobile technologies. This poses a challenge to the developers of the system, as cryptography algorithms often require relatively large amounts of processing power and memory to function. In some systems it might be outright impossible to implement cryptographic data protection, e.g. in systems based on passive RFID tags, due to the lack of computational capabilities in these tags. Lightweight cryptography is an area of research which deals with implementing secure data transfer in environments where resources are limited, such as positioning systems. [5][11]

Threats to the correct functionality of a positioning system include both unintentional interference from other devices as well as deliberate attacks against the system. Possible forms of attack are determined by the system architecture and the medium used for data transfer. Examples of deliberate interference against RF-based systems include spoofing, where a device falsely broadcasts itself as a node in the network, jamming, where the signals of the system are weakened, leading to incorrect positioning results, and malicious node attacks, where nodes provide random or partially incorrect data. Poor implementations of otherwise well designed cryptography algorithms may open up opportunities to perform attacks on the system with the goal to break the encryption. Which aspects require the most attention are, once again, dependent on the system architecture. If the devices performing the encrypting are connected to the Internet, it opens up the possibility to perform timing attacks, which are possible if the algorithm used is not performed in constant time. These attacks are based on the fact that if the time to perform the encryption is dependent on the size of the data to encrypt, knowing the time taken also reveals the size of the data, which greatly reduces the effort needed to decrypt it. If the potential attackers have physical access to the encrypting device, analysis of power consumption or temperature can reveal similar characteristics of the data. These types of attacks are both known as side-channel attacks. [11]

Approaches for protecting the privacy of people being tracked that are implemented on the service-level include the anonymization and obfuscation of collected data. These methods decrease the sensitivity of the data, reducing the potential damage caused in case of unauthorized access to the data. An example of anonymization includes the masking of the Media Access Control (MAC) addresses of devices, which is the main distinguishing piece of information gathered by RF-based positioning systems. This is done by transforming the address through a replicable and irreversible process, maintaining the possibility to tell different devices apart without compromising the privacy of the users. Obfuscation means deliberately introducing an amount of error into the collected data, making the subject more difficult to identify through analysis of the data. Both approaches have their disadvantages. Personalization of services through positioning information is becoming increasingly popular, but anonymization limits the possibilities to personalize the services. Obfuscation on the other hand degrades the quality of services, and may make some services which rely on accurate data unusable. [5]

# 3 Methods and theory

## 3.1 Modeling indoor space

Models are formal representations of the area where data has been gathered. The data is fitted to these models to gain a simplified view of the data, and to apply analytical methods which require the a specific formal representation. As an example, many models represent the area as a graph, which allows the use of graph algorithms when analyzing the data after fitting it to this model. The models used for indoor spaces can be seen as an extension to their more extensively studied outdoor counterparts. On an abstract level, models for outdoor and indoor spaces are very similar, as e.g. both a road and a corridor can be generalized to a path. However, differences emerge in how structural information is represented, as outdoor spaces consist of both natural and man-made obstacles, while indoor space is focused on e.g. walls, doors and windows. [9]

The choice of model depends on the goal of the analysis and the requirements of the chosen methods. The types of models can roughly be divided into two categories: semantic models and spatial models. Semantic models are focused on the properties of entities in the space and relationships between these, while spatial models are focused on the connectivity and structure of the space. Spatial models can further be divided into topological models and geometric models. Topological models contain information on both the structural space and the path space of an environment. [9]

In literature within the field of indoor positioning, the line between geometric models and the topographic space represented in topological models is often blurred, and the two are used as synonyms to each other. For the context of this thesis, topographic space will refer to structural information for e.g. walls and doors as limiters of mobility, while geometric models will refer to models focused on the shapes of the structures and objects in the indoor environment being modeled. In the following sub-sections, the most common categories of models will be presented along with examples of cases in which they may be used.

### 3.1.1 Semantic models

Semantic models represent high-level information about an environment, such as landmarks or equipment present in a room. This type of information is relevant in human navigation systems [2] and other systems where human-machine interaction is important, e.g. in the case of service robots [23]. Semantic models are often used in conjunction with topological or geometric models, either separately or by integrating the relevant semantic information into the other models used. Semantic models are often based on relations, and rooms being connected to each other by a door can be seen as a relation and certain objects or activities can be seen as related to certain rooms. As an example, a stove could be associated with the "kitchen" type of room, and the activity of working might be associated with the "office" type of room. Examples of models for utilizing this kind of information include the one proposed in [23], where conceptual information about rooms and objects are used to categorize those present in the space being analyzed, and the one proposed in [14], in which a graph-based approach to linking rooms and doors with the locations of static and moving objects is presented. A common element among semantic models is that conceptual information about the space is often kept separated from the representation of the actual physical space in order to allow for generalizations and to create a model closer to how a human perceives space.

### 3.1.2 Topological models

Topological models are spatial models focused on the connectivity of a space, and there are generally two aspects of indoor space being represented in these models: the *structural space*, showing the walls, doors, windows etc. of the space, and the *path space*, which shows the paths which exist in the space. The terms primal space and dual space are often used as alternative terms for the structural and path spaces, respectively. Topological models are commonly used for indoor tracking applications. Path space is often represented by means of various graphs. There are several types of graphs used for this, which take different aspects of indoor space into account. The graphs take either the connectivity of the space or the accessibility of the space into account, with connectivity meaning that there is a physical means of passage between two locations, while accessibility also takes into account one-way passages such as security checks. The connectivity of a space can be modeled using an undirected graph, while accessibility requires a directed graph. If the model will be used in a path-planning application, the edges may also have weights assigned to them. The models can either be two- or three-dimensional, e.g. a topological model of a multi-story building can either be modeled fully in 3D or as several linked 2D-models. An example of an undirected graph model of path space can be seen in illustration 2. [9]

Another aspect where the graphs may differ is the level of detail with which they track the movement of the entities. In a path-based approach the nodes of the graph model represent intersections along the path, while in a cell-based approach, the nodes of the graph represent the rooms (cells) the tracked entity is located in at the moment. If a cell-based approach is used, partitioning sensors are often placed at the doors already in the system design phase, in order to be able to determine the room the entity is located in with greater accuracy. [36]

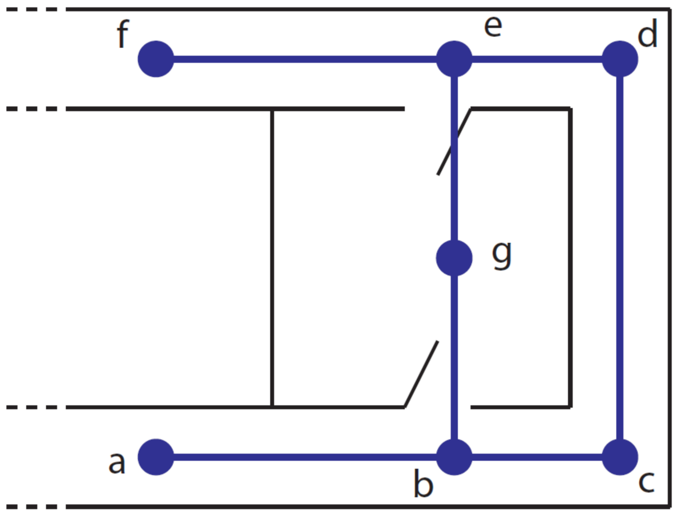


**Illustration 2:** An example of a topological graph model. This model accurately conveys the path space of the area by assigning each intersection and point of interest its own node. A path planning application is a possible use case for this type of model. **Source: [9]**

### 3.1.3 Geometric models

Geometric models are spatial models which focus on the structure and shape of a space. This type of models is used for e.g. construction and building planning [9], and computer vision [37]. Camera-based positioning systems can also utilize this type of models as a reference when determining the position of detected entities in the area [15]. In contrast to the topological models, the generation of geometric models is largely automated. The generation of these models is closely related to automatic indoor mapping, with the main difference being the intended use for the model. The models can be created based on images [37], or using various sensors. There exist applications based on depth sensors for creating these models using both consumer range sensors such as the Microsoft Kinect [29], and those using high-end sensors such as Lidar [38].

### 3.1.4 Hybrid models

In many cases, a single type of model is insufficient for the case being studied. While landmark-based human navigation systems may be able to work simply using semantic information [2], semantic information is often combined with topological or geometric information. In the case of robotics, semantic information is often combined with geometric information from sensors and a logical model of the environment created based on this information [23]. There also exist layered models, where the same space is represented by several connected models of different types. An example of a layered model is [39], where geometric and topological information are placed on different layers. Information from different types of sensors also receive their own layers in this model.

## 3.2 Geometric methods

Various geometric methods for measurement of position and distance have been used since ancient times, but it was not until the 16th century that the modern surveying methods of triangulation and later trilateration came into use. They revolutionized the mapping industry, as these methods allowed maps to be created with an accuracy far greater than before. Triangulation and trilateration are both methods within geometry and trigonometry, used to obtain exact measurements of distance and position by utilizing the properties of triangles and circles. Triangulation uses angles to measure the distance to a target location, while trilateration uses known distances for calculating the location of a point. Nowadays, trilateration is often the method of choice for surveying, as the accuracy of the equipment used to measure distance has improved remarkably since these methods were first taken into use. [40][41][42]

The methods used for triangulation and trilateration are applicable in any dimension, but real-world applications are focused on the second and third dimensions. The number of required reference points required increases with the dimensionality. Triangulation uses two reference points when applied in the second dimension and three in the third dimension. Trilateration requires one additional reference point, meaning it uses three points when applied in the second dimension and four when applied in the third dimension. Both two- and three dimensional triangulation and trilateration are used within indoor positioning. [1][42]

Triangulation and trilateration are very similar when applied in practice, with the main difference being that within triangulation the angles are measured and the distances computed, while the opposite is true for trilateration. Both methods provide exact measurements, provided the parameters used are correct. However, in real-world applications there is always a degree of uncertainty due to the limited accuracy of the used instruments or due to measurement errors. The choice of method boils down to which information is available, and which information is deemed to be most reliable for the case being studied. Nowadays, trilateration is often the method of choice, as the accuracy of equipment used to measure distance has surpassed that of angle-measuring equipment. [41][42]

### 3.2.1 Triangulation

Triangluation, or simply angulation, is a method for obtaining the distance to a target location through the use of reference points with known positions, and the distance between these points. In two dimensions, two reference points are required to perform these calculations. When lines are drawn between the reference points and the target point, a triangle is formed. By measuring the angles between the line formed between the reference points and the lines between the reference points and the target point, the distance between the target point and each reference point can be calculated. From the calculated distance, coordinates can also be determined for the target location. [1]

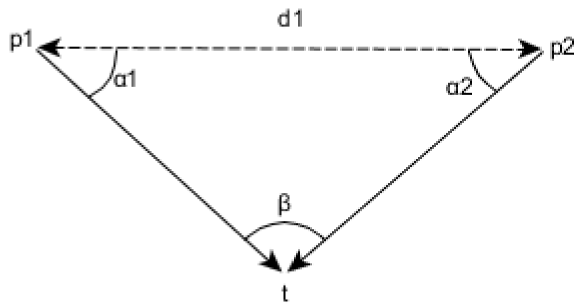


**Illustration 3:** An example of triangulation. The reference points $p1$ and $p2$ have known locations, and the distance $d1$ between these points is also known. The angles $\alpha 1$ and $\alpha 2$ are also known. Using this information, the angle $\beta$ and the coordinates of the target point t can be calculated.

An example of two-dimensional triangulation can be seen in illustration 3. Lines are drawn between the reference points $p1$ and $p2$, and the target point $t$, forming a triangle. The distance $d1$ between $p1$ and $p2$ is measured, or calculated in case the coordinates of $p1$ and $p2$ are known. This side of the triangle is called the *baseline*. The angles $\alpha 1$ and $\alpha 2$ in the corners of the triangle located at the respective reference points are measured. The angle $\beta$ in the corner at $t$ can then be calculated as $180° - \alpha 1 - \alpha 2$. To obtain the distance between the reference points and the target point, and the coordinates of the target point, the triangle must first be split into two right angled triangles, whose hypotenuses, i.e. the distances between each reference point and the target point, can be obtained using the Pythagorean theorem. [42]

Applying triangulation in three dimensions is similar to two dimensions, but three reference points are used instead of two. This results in three baselines being formed, and six angle measurements are required to obtain the coordinates of the target location. However, available information about the case being studied is often used to reduce the amount of required measurements and computations. As an example, obtaining points directly above or below the target point can be done with only two reference points and three angle measurements. A case of this, which is a common textbook example of triangulation, is to measure the height of a distant object which would otherwise be too difficult to measure. The location of the base of the object to measure can be obtained through 2D triangulation, and the top of the object to measure is known to be located on a line perpendicular to the lines formed between the reference points and the base of the object. Therefore, 2D triangulation can be applied again to obtain the location of the object's top, with only one additional vertical angle measurement from either reference point required. [1][43]

### 3.2.2 Trilateration

Trilateration, or simply lateration, is a method for obtaining the exact coordinates for a position when the distances between this position and reference points are known. The coordinates of these reference points must also be known. Trilateration can be applied in any number of dimensions, with the two and three dimensional versions being used for real-world applications. In two dimensions, three reference points are required, and the coordinates for the target position are obtained by creating circles around the reference points, and the lengths of the radii of these circles are determined by the known distances between the reference points and the target location. In three dimensions, spheres are used instead of circles. [22][44]

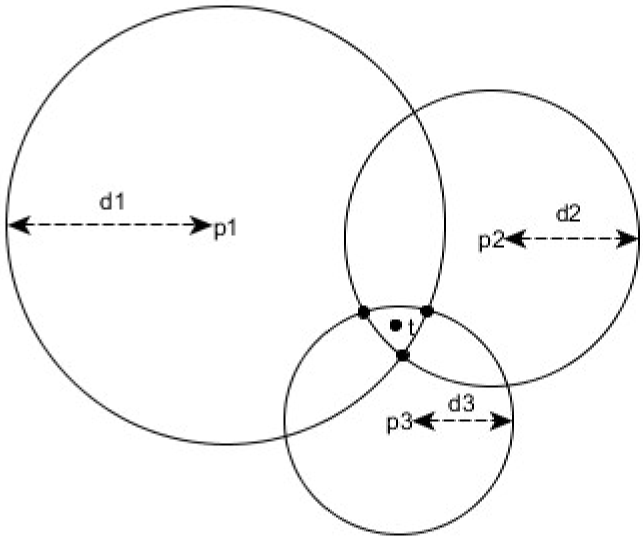


**Illustration 4:** An example of trilateration. Points *p1*, *p2* and *p3* are the reference points with known coordinates, and distances *d1*, *d2* and *d3* are the measured distances between the reference points and the target point. As no directional information is available, circles are drawn around the reference points, with the measured distances being the radii of these circles. This information is then used to obtain the coordinates of target point *t*.

An example of trilateration is given in illustration 4. Here, the reference points $p1$, $p2$ and $p3$ with known coordinates are used to obtain the coordinates of a target location $t$. Distances $d1$, $d2$ and $d3$ are the measured distances between the target location and the respective reference points. These distances are used as the radii of circles drawn around the reference points. Ideally, these circles would have a common intersection point, which would be the location of the target point. However, in most real world cases and also in this illustration, no such common intersection point exists. Instead, the location of $t$ is calculated as the average of the pairwise intersection points between the circles.

In three dimensions, the calculations are similar, but four reference points are required instead of three, and spheres are used instead of circles. The intersection area of two intersecting spheres is a circle. By adding a third sphere, another circle is formed, and the possible locations are narrowed down to where the two circles intersect, i.e. two points. By adding a fourth sphere, a third circle is formed, and the position of the object can be pinpointed. In practical cases, it may be possible to simplify this process to only use three reference points, if one of the possible positions obtained is always known to be incorrect. This is the case with GNSS systems, as one of the possible locations will always be far out in space while the other one is on the surface of the Earth. In indoor positioning, however, this may not be the case as the signal transmitters may be both above and below the target, e.g. in a multi-story building, making it difficult to always identify which of the two possible positions is false. [44]

## 3.3 Markov chains

A Markov chain is the graphical representation of a stochastic process called a Markov process, named after the Russian mathematician Andrey Markov. The characteristics of a Markov process is that it has no memory, meaning only its current state determines its next step. In a Markov chain each node represents a state in the process, and directed edges between the nodes represent the possible transitions between nodes. Each edge has a value which represents the probability of that particular transition occurring. A Markov chain always has a finite number of states, though Markov processes do not have this limitation. An example of a Markov chain can be seen in illustration 5. [45]

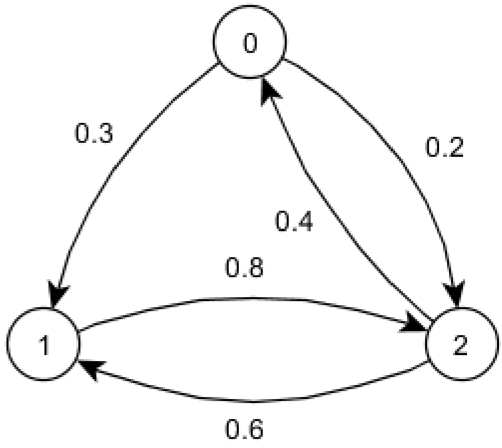


**Illustration 5:** An example of a Markov chain. The nodes represents the states of the process, and the edges represent the probability of moving from one state to another. Edges from nodes to themselves have been omitted.

There are generally two main types of Markov processes: *discrete-time* and *continuous-time* Markov processes. The progression of a discrete-time Markov process happens in steps, while the state changes in a continuous-time Markov process occur at random intervals according to some distribution. Many real world phenomena can be modeled as Markov processes, with common examples including gambling, virus mutations and customer behavior. An example of a discrete-time Markov process is a board game where the state of the game only changes whenever a player takes a turn. An example of a continuous Markov process is one which models how many customers have visited a store after a certain time, when the customers visit at random intervals. [45]

The "memorylessness" of Markov processes is called the *Markov property*. There also exists a property called the *strong Markov property*, which is similar to the Markov property, but defined in terms of a random *stopping time* for the process rather than simply stating that the future states of the process are only influenced by the current state of the process. To satisfy the strong Markov property, a process stopped at any random time should not have its next steps influenced by the path taken to the current state, only by the state itself. In the case of discrete-time Markov processes, the "weak" Markov property implies the strong Markov property, but this is not the case for continuous-time Markov processes. The strong Markov property always implies the Markov property. [45]

### 3.3.1 Formal description of Markov chains

In this section, a formal definition of Markov chains will be given along with explanations of the mathematical concepts used in this definition. The definition of Markov chains is usually given in terms of a *transition matrix* over a discrete *state-space*. The transition matrix consists of *distributions* which represent the probabilities for moving between states. A state-space $I$ is a countable set in which each $i \in I$ is called a state. A distribution $\lambda = (\lambda_i : i \in I)$ shows the probability for transitioning to each state, and has the properties $0 \le \lambda_i < \infty$ and $\sum_{i \in I} \lambda_i = 1$. A transition matrix $P$ is a matrix of size $n \times n$, where $n = |I|$ and in which every row is a distribution. Informally, the elements of this matrix represent the probability for moving from the state represented by the element's row to the state represented by the element's column. This type of matrices is also known as stochastic or Markovian matrices. An example of a transition matrix over a state-space is given in equation 1. [45][46]

$$I=\{0,1,2\} \quad P=\begin{pmatrix} 0.5 & 0.3 & 0.2 \\ 0.0 & 0.2 & 0.8 \\ 0.4 & 0.6 & 0.0 \end{pmatrix}$$

**Equation 1:** The state-space and transition matrix of the Markov chain shown in illustration 5. The rows of the matrix represent the states of the process, and the values represent the probability for moving from that state to the state given by the collumn. The sum of the values in each row is always 1.

Several concepts from the field of probability theory, to which stochastic processes belong, are required to provide the formal definition of Markov chains. A probability space $(\Omega, F, \mathbb{P})$ is one of these concepts, and will be used throughout the definition. In the probability space, $\Omega$ is the sample space, which is the set of all possible outcomes. The set $F$ contains events, which are sets of outcomes. $\mathbb{P}$ is a function mapping these events to probabilities. Random variables are functions which return a random value in $\Omega$ according to the probabilities given by $\mathbb{P}$. For Markov chains, the random variable $X$ is defined as a function $X : \Omega \to I$, mapping outcomes to the states of the process. A Markov chain can then be defined as a sequence $(X_n)_{n \ge 0}$ of $I$-valued random variables with the transition matrix $P$. [45][46]

$$\mathbb{P}(X_0=i_0, X_1=i_1, \ldots, X_n=i_n)=\lambda_0 P(i_0, i_1) P(i_1, i_2) \ldots P(i_{n-1}, i_n)$$

**Equation 2:** The definition of a discrete-time Markov chain.

The formal definition of a discrete-time Markov chain is given in equation 2. The left-hand side of the equation defines the possible outcomes as finite sequences of random variables which can take on values corresponding to the states in $I$. The right-hand side provides the probability of each value in the sequence according to the previous value, given by the corresponding value in $P$.

In other words, the probability to transition from the current state $i_{n-1}$ to the next state $i_n$ is given by $P(i_{n-1}, i_n)$. As an example with the transition matrix provided in equation 1, given that the process is in state $i_{n-1} = 1$, the probability for moving to state $i_n = 2$ is obtained from the element at $P(1, 2) = 0.8$.

### 3.3.2 Common uses

Markov chains have many applications and are used in a large variety of fields, due to the high amount of real-world processes which satisfy the Markov property. Moreover, systems with high complexity are often better modeled through randomness rather than by attempting to accurately model them mathematically. Examples include the study of biological processes, natural language analysis and resource management. Examples within biology include the modeling of virus mutations, population development and the spread of epidemics. In natural language analysis, Markov chains are used to analyze how symbols are distributed in a text or the word usage of a specific author. In resource management and other corporate business activities, Markov chains are often used to quantify the risk of e.g. an investment. In the case of this thesis, they are used to identify the most commonly occurring paths through the areas being examined. [45]

A popular application of Markov chains is within a class of algorithms called Monte Carlo methods. Monte Carlo methods utilize random sampling to obtain an approximate solution to a broad range of problems which would be difficult or impossible to solve otherwise. When utilizing Markov chains for Monte Carlo computations, they are often labeled Markov chain Monte Carlo (MCMC) methods. The goal of Monte Carlo methods is to obtain samples of the distribution of a random variable, and to use these samples calculate an expected value for this value. In cases where simulating the distribution is difficult, MCMC can be used to simulate samples from the distribution with less computational complexity than simulating the actual distribution. An example of the use of MCMC methods within the field of indoor positioning is [47], where an MCMC method is applied to estimate the locations of people in an indoor environment. [45][46]

# 4 Case study

In this section, the case study performed for this thesis will be presented, including the experiment setup, the data set and the chosen methods of analysis. The case being studied is an indoor people-tracking problem, where the movements of medical personnel are analyzed to evaluate the efficiency of an information system. The goal is to evaluate whether this type of analysis provides results which can be used to draw conclusions about the working efficiency of the personnel or the efficiency of the system. Graphical visualizations of the data were used for analysis and for presenting the results. However, due to the sensitivity of hospital maps and data, in this thesis the results will be presented in table form only, with the rooms anonymized.

The representation which eventually was chosen for the data is a symbolic one, where the rooms of the site make out the set of discrete positions the tracked entities can be located at. The sites are modeled topologically as graphs of rooms. The path spaces of the sites are not explicitly defined. Rather, the paths which exist within the data determine which rooms are connected and which are not. Three methods were chosen for analyzing the data, and they are the creation of Markov chain models of the sites, calculating average weeks for each room of the sites and calculating the average visit lengths for each room. All of these methods provide representations of the data which are independent of the size of either data set used to create them. In the following sections, the experiment setup and the used data set will be presented, followed by a more detailed description of the chosen methods and reasoning behind these choices.

## 4.1 Overview

### 4.1.1 Experiment setup

This section will describe the experiment setup and the positioning system which has been used to gather the data which has been analyzed. The data had already been collected when the writing of this thesis started, and the collection process is not a part of this case study. The system used to gather this data was a RF-based remote positioning system using Bluetooth technology. The used beacons were Bluetooth Low Energy (BLE) beacons. These static beacons were placed at designated locations in the hospitals, and the phones carried by the personnel detected their presence. The phones were using the Android operating system, and the readings were made using the Android Beacon Library4-application. The phones were set to perform readings of the beacons at 30-second intervals.

The data comes from two different studies which have both been performed with a similar setup. The first one is the accident and emergency department (Finnish: *päivystyspoliklinikka*, PPKL) study, which has been performed in three different hospitals, with five collection periods in each hospital. The hospitals in which this study has been performed are the Vaasa, Pori and Rovaniemi hospitals. In this study, the information system under evaluation has been in use during the three final collection periods. The collection periods for the PPKL study are presented in table 1, with dates included. The second study is the emergency room (Finnish: *päivystysosasto*, PO) study, which has been performed in the Vaasa hospital with four different collection periods. The information system was present during all collection periods except the first. The collection periods for the PO study are presented in table 2. In both studies, two devices have been present and tracked in each hospital.

| Collection period | Date | System status |
|---|---|---|
| 1 | 1.6.2015 - 30.6.2015 | Not implemented |
| 2 | 15.2.2016 - 15.3.2016 | Not implemented |
| 3 | 1.6.2016 - 30.6.2016 | Implemented |
| 4 | 15.8.2016 - 26.9.2016 | Implemented |
| 5 | 15.11.2016 - 15.12.2016 | Implemented |

**Table 1:** The different periods during which data was gathered in the PPKL study. The same periods apply to all three hospitals.

| Collection period | Date | System status |
|---|---|---|
| 1 | 1.2.2016 - 14.3.2016 | Not implemented |
| 2 | 18.4.2016 - 39.5.2016 | Implemented |
| 3 | 15.8.2016 - 26.9.2016 | Implemented |
| 4 | 1.11.2016 - 13.12.2016 | Implemented |

**Table 2:** The different periods during which data was gathered in the PO study.

### 4.1.2 Terminology

This section will present the terms which will be used to refer to different aspects of the data consistently throughout the sections relating to the case study. The terminology used for different aspects of the raw data is as follows: An *observation* will refer to a reading the phone has made, and consists of information about all the detected beacons as well as a timestamp when the reading was made. Unless stated otherwise, the position of the device will refer to the position of the beacon closest to the device at a given observation, according to the proximity-based approach. An empty observation is one in which no beacons were detected, and which will be pruned away. A *transition* will refer to two subsequent observations made by the same device.

The data is preprocessed into a more abstract format better fit for analysis. Definitions and reasoning behind the choices related to the preprocessing will be presented in the preprocessing section. The terminology used to refer to different aspects of the preprocessed data is as follows: A *room* is defined as a group of beacons which are grouped together to represent a room in the area. A *visit* to a room is defined as the chain of transitions which occur only between the beacons belonging to a specified room. The timestamp of the first observation in the visit will be considered as the start time of the visit. A *room transition* refers to two subsequent visits. A *session* will refer to a period in which the phone is considered to be active, and can be seen as a chain of visits or room transitions.

### 4.1.3 Data set

The data set used for this thesis comes from two studies. However, the collection setup and data format is identical throughout both studies. In each of the hospitals where data has been gathered, two devices carried by medical personnel of different professions have been tracked. The amount of data collected at each site, and the periods during which data was collected is presented in table 3. In the PPKL study, the first device has been carried by a physician, and the second device has been carried by a nurse. In the PO study, the first device was carried by a nurse and the second one by a physician for the first two periods of the data collection, and they were switched for the remaining two periods. This has been taken into account during analysis. For clarity, the devices which have been present at a site will henceforth be referred to as the physician's device and the nurse's device for both studies. The tracked entities are only identified by their profession, and multiple professionals have carried each device throughout the studies.

| Study | Site | Device 1 | Device 2 |
|---|---|---|---|
| PPKL | Vaasa | 102008 | 131639 |
| PPKL | Pori | 111948 | 242707 |
| PPKL | Rovaniemi | 97298 | 122163 |
| PO | Vaasa | 59265 | 122675 |

**Table 3:** The total number of observations for each device at the different sites for both studies.

The data was provided in a JSON-format. The data is structured as a list of observations, with each observation having a time stamp, an identifier for the hospital the observation was made in, and a list of beacons which the phone hears at that given point in time. For each beacon the device hears, there is information such as an identifier for the beacon, a calculated distance metric and various information on which the calculation is based, including RSSI. Beacons are identified by a site ID and a beacon ID, with the positions of all relevant site ID / beacon ID combinations being known.

## 4.2 Preprocessing

The first step of preprocessing was to identify and prune superfluous and erratic data from the data set. First, all irrelevant devices which the phone had heard were removed. These were identified by comparing the identifier used as a site ID against the known site IDs. Second, all empty observations were pruned. Empty observations occur due to the phone being on and listening for beacons but no beacons being heard. The most probable explanation for such readings occurring is that the phone has been temporarily away from the site, or in a part of the site where no beacons are present. All transitions from nodes to themselves were also removed. This was done due to how the readings did not always occur at the specified 30 second intervals, making them an unreliable measure of time spent at a location. Instead, the timestamps of the observations were used for this.

The next step was to identify periods of inactivity and to remove them from the data set. Activity was defined as a period in which the time between the observations of a transition does not exceed 30 minutes, and during which the beacon closest to the phone changes at least every 120 minutes. These time limits are based on acquired domain knowledge of the area being analyzed, and may need to be adjusted for other cases. Based on these limits, the data was split into sessions. All sessions shorter than 5 minutes were removed.

The final step was to define the data in terms of rooms and visits rather than observations and transitions. Rooms were created by manually grouping together beacons which were present in the same physical space. This additional layer of abstraction was added due to how periods of inactivity in rooms with several beacons in them often went unnoticed with the definition of activity given above. This is likely due to the signal easily being disturbed by mobile entities in the room, causing the phone to appear to be moving even when it is still. That the room the phone is in must change at least every 120 minutes was added to the definition of activity, and the sessions were readjusted according to this. Sessions which ended up being too short after this were removed.

Based on acquired domain knowledge for the hospitals, the data is also split into two sets according to weekday and time of day, and these partitions will be analyzed separately. The first one is named *normal time*, and is defined as the data which has been gathered from Monday to Friday, between 8:00 and 15:00. The second one is named *on-call time*, and is defined as the data which has been gathered on Saturday and Sunday at any time of day, or Monday to Friday from 15:00 to 8:00.

## 4.3 Approach and rationale

The choice of selecting proximity-based positioning over coordinate-based positioning was made after weighing the benefits and disadvantages of the two approaches against one another. The information available in the data which was deemed interesting was the amount of traffic each part of the site receives, the time spent in each part of the site, the path choices of the tracked entities, and lastly the actual distance walked by the tracked entities. For analyzing all but the last of these four aspects of the data, a symbolic representation of the sites appeared as the most fitting way to model the area. The advantage of symbolic positioning is that graphs created using this representation have a low level of complexity, facilitating analysis. For both approaches, this would require a manual partitioning of the sites. For proximity-based positioning, this amounts to assigning each beacon to a partition, while for coordinate-based positioning requires geometrical areas representing the different partitions to be defined, with the latter being more time-consuming. The benefits of using coordinates is being able to utilize all of the available information, at the cost of the time required to implement the additional intermediary steps. Due to time constraints, the choice to only focus on the proximity-based approach was eventually made, leaving the information on walked distance unutilized.

Three approaches for utilizing each of the remaining three aspects of the data were chosen. The goal of the chosen approaches was to model patterns in the data in a way which allows the periods before and after the system's implementation to be compared, and a quantifiable difference to be obtained. Due to how the amount of days which have data and the amount of observations per device varies greatly between the periods being compared, the constraint that the chosen methods must be independent of the differences in the amount of data available between the periods was defined. The first of the methods which eventually were chosen is the use of Markov chain models, which were chosen to represent the path choices of the tracked personnel. The second chosen method was to create average week models consisting of the average amounts of visits each room receives on different weekdays, in order to show the amount of visits each part of the site receives. The final chosen method is to calculate the average visit duration for each room for the periods, in order to utilize the time information in the data. The following sections will describe each approach and the reasons for selecting them for this case.

### 4.3.1 Markov chains

In the approach using Markov chains, Markov chain models for the periods before and those after the system's implementation are created. The Markov chains are used as probabilistic transitional models of the area, created based on the room transitions which occur throughout the area. Separate models are created for normal time and on-call time. The rooms of the area make out the states of the Markov chains. The different possible paths between the rooms will not be considered separately. The Markov chains are created by taking the number of transitions out from a room and calculating for each edge separately how great their part is of all the transitions out from that room. The created graph can then be examined for edges with both a large number of traversals and a high probability of being traversed from the connected nodes in order to locate various paths of interest in the graph.

The Markov chains satisfy the requirement of being independent of the amount of data in the data sets, as the values in the chain are percentages of the transitions going out from each room.

Markov chain models for different periods can be subtracted from one another to obtain a graph describing the difference between the models. This difference shows the changes which have occurred in the transitions going out from the different rooms, implying changes in path choices or traffic to certain areas. One weakness of these models is the fact that these models do not deal with the actual amounts of transitions occurring, as rooms which have a low amount of visits are likely to display greater fluctuations, as a small change may be large in relation to the previous values. Therefore, the information in these models is most useful when one has specified rooms of interest in mind.

### 4.3.2 Average weeks

In the approach of analyzing the data through average weeks, average weeks are specified for the site before and after the system's implementation. This average week model is created by calculating the average amount of visits for each room separately for each day of the week. Average weeks are created for both normal and on-call time, with an average week for normal time consisting of 5 days and an average week for on-call time consisting of 7 days. When creating the model, the average for a specific room on a specific day is only affected if the phone has been active during that day, meaning zero visits to a room will only affect its average number of visits if the device has visited other rooms in the area during that day. This model satisfies the requirement of being independent of the amount of data available for each period, while still preserving an overview of the actual amount of visits each room receives. Similarly to the Markov chain models, the average weeks can be subtracted from one another to obtain a view of the difference between them. It should be noted that the week for on-call time will have values based on a lesser amount of hours for the days Monday through Friday than for the weekend. This should be taken into account when comparing the days with one another.

### 4.3.3 Average visit durations

The final model was chosen to make use of the information available on the duration of each visit, and consists of the average visit durations for each room over a certain period of time. The averages satisfy the requirement of being independent of the differences in the available amounts of data for each period. Similarly to the previous models, they can be subtracted from one another to obtain a difference. Unlike with the visit counts, these averages are not calculated separately for each weekday. The reason behind this is how the visit durations suffer more from sparsity of data than the visit counts. This is partly because the durations of the visits have a much greater variance than the amount of visits, causing outliers to distort the view of the data to a greater extent when the amount of visits to a room is low. Moreover, if a room would not have any visits for one of the periods, a difference between the averages would not be possible to calculate. First splitting the data into normal and on-call time, and then further splitting into separate weekdays was deemed to make the visits too sparse for such a representation.

## 4.4 Implementation

All the processing of data and algorithms used are implemented in Python 2.7.13. The code was run on a computer with an Intel Core i7-6700K processor and 16 Gigabytes RAM. The operating system used was Windows 10 x64. In addition to the code for the preprocessing and approaches for analysis, a custom solution for parsing the JSON files was created due to the files being too large for Python's native JSON parser. The code is stored in the GitLab repository of Åbo Akademi University.

# 5 Results

In this section, the results gained from creating the specified models based on the data are presented. The results presented here are the calculated differences between the models before and after the system's implementation. The full models upon which these differences are based are not included in this thesis. Rather, they are available in the GitLab repository of Åbo Akademi University. In the presented differences, positive values indicate an increase from the time before the system's implementation to the time after, while negative values indicate a decrease. Data on devices during some periods in some of the sites appear erratic, and the differences presented here do not include those which would be based on this data. The affected parts of the data are the physician's devices in the Vaasa and Pori hospitals for the PPKL study, during the time after the system's implementation, as well as all data for the physician's device in the Vaasa hospital for the PO study. In addition, some beacons were lost or otherwise ceased to function correctly during the experiment. Rooms affected by this are removed from the results.

## 5.1 Markov chains

In this section, the most notable differences between the transition matrices of the Markov chains which have been created for the sites for the periods before and after the system's implementation are presented. Markov chains have been calculated for all devices, separately for normal time and on-call time. Comparisons created by subtracting the transition matrix from the time before the system's implementation from the one from the time after the system's implementation have been created, and are presented here. While these models are built from percentages rather than the actual amount of visits, the amount of rooms a room is connected with (i.e. the amount of rooms which shows some difference in traffic) can be seen as a measure of the room's relevance. Rooms which have their values affected by missing or malfunctioning beacons have their values grayed out.

Due to the size of the transition matrices, they are all placed in *Appendix A* rather than being included in this section, meaning all the tables referenced in this section are located in this appendix. Key parts of the results will be noted here in text form, however. The differences between the Markov chain transition matrices for the nurse's device in the Vaasa hospital PPKL study are presented in tables 13 and 14. One notable change which can be seen is with the traffic in room *w*, which appears to be connected to most other rooms in the site. The incoming traffic to this room shows greater changes than the outgoing traffic. This trend is milder in on-call time than in normal time. Other noteworthy rooms include *x* and *am*, which also appear to be connected to most other rooms on the site, but which have smaller differences between the periods. The differences between the Markov chain transition matrices for the nurse's device in the Pori hospital, normal and on-call time, are presented in tables 15 and 16 respectively. Rooms *q*, *r* and *ae* are grayed out as the beacons representing these rooms appear to have erratic data. Notable differences include a sharp decrease in incoming traffic to rooms *n* and *v*, and an increase in incoming traffic to rooms *o* and *p*. Nextm the results for the Rovaniemi hospital are presented. The results for normal and on-call time for the physician's device are presented in tables 17 and 18, and the results for normal and on-call time for the nurse's device are presented in tables 19 and 20. The data for room *k* is grayed out due to the beacon representing this room displaying erratic data for the period after the system's implementation. Lastly, the differences between the Markov chain transition matrices for the nurse's device in the Vaasa hospital PO study, normal and on-call time, are presented in tables 21 and 22. Rooms *r* and *j* display a trend of decreasing outgoing traffic in both normal and on-call time. Strong fluctuations can be seen in the incoming traffic to room am, with most of the incoming traffic during on-call time coming from room *z*, while normal time does not display this kind of concentration to one room.

## 5.2 Average weeks

This section presents the calculated differences between the created average week models for the time before and after the system's implementation, for each device in each hospital. In each of the tables, a negative value indicates that the average amount of visits on the day signified by the column, to the room signified by the row has decreased from the time before the system's implementation to the time after the system's implementation. A row with hyphens instead of values indicates that a beacon representing the room has gone missing during the experiment, and the difference for this room should not be taken into consideration for any conclusions. A column with hyphens instead of values indicates no beacon has detected any activity from the device in question during that weekday over the course of either the period before or the one after the system's implementation.

First, the average weeks calculated for the Vaasa PPKL and Pori data sets are presented in table form. The average week differences for the nurse's device of the PPKL study in the Vaasa hospital can be seen in table 4. Strong increases can be seen for rooms *b*, *c* and *am*, and a medium increase can be seen for rooms *w* and *x*. The average week difference for the nurse's device in the Pori hospital can be seen in table 5. Readings for rooms *q*, *r* and *ae* are erratic for the periods after the system's implementation, and the information for these rooms is not included in the results. The most notable differences which can be seen in the table are an increase the amount of visits to rooms *o* and *z*, and a decrease in the number of visits to rooms *v* and *w*. Differences can be seen between on-call time and normal time as well. Sharp increases in the number of visits for rooms *p* and *u* can be seen for normal time, while on-call time has the amounts close to unchanged. The room *ad* has an increase in the amount of visits for normal time, while a slight decreasing trend can be seen for on-call time.

| | On-call | | | | | | | Normal | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| room | MON | TUE | WED | THU | FRI | SAT | SUN | MON | TUE | WED | THU | FRI |
| a | 2,20 | 2,18 | 5,33 | 3,76 | 3,37 | 9,13 | 4,50 | 2,20 | 4,10 | 2,93 | 1,52 | 3,40 |
| b | 24,50 | 12,11 | 17,00 | 32,29 | 26,83 | 43,17 | 34,43 | 16,55 | 16,05 | 8,54 | 18,25 | 21,60 |
| c | 19,35 | 8,00 | 6,69 | 35,11 | 22,60 | 43,20 | 12,90 | 11,95 | 14,90 | 3,46 | 15,15 | 18,65 |
| d | 6,85 | 4,89 | 4,38 | 9,02 | 6,23 | 14,70 | 2,47 | 3,15 | 0,65 | 0,50 | 4,18 | 8,15 |
| e | 0,60 | 0,86 | 0,11 | 0,22 | 0,30 | 0,40 | 0,00 | 1,30 | 0,40 | 0,14 | 0,12 | -0,20 |
| f | -1,20 | 0,93 | 1,36 | 0,16 | 0,90 | 1,50 | 0,30 | 6,80 | 2,15 | 0,39 | 0,05 | 1,85 |
| g | -1,30 | 1,36 | 3,04 | 1,36 | 1,17 | 2,27 | 1,07 | 7,00 | 1,25 | 2,00 | -2,22 | -2,05 |
| h | 0,15 | -1,25 | 0,44 | 0,11 | -0,70 | 0,40 | 0,33 | 0,30 | -0,05 | 0,00 | -0,08 | -1,55 |
| i | 0,35 | -0,07 | 1,04 | -0,09 | -1,67 | 0,30 | -0,20 | -0,90 | -0,95 | 0,14 | -2,22 | -1,55 |
| j | -1,40 | -1,36 | -0,20 | -1,51 | -7,70 | -3,90 | -0,93 | -2,65 | -2,70 | -1,25 | -7,58 | -7,05 |
| k | 1,00 | 0,43 | 0,13 | 0,22 | 0,57 | 0,80 | 2,00 | -0,15 | -0,05 | 0,14 | 0,88 | 1,20 |
| l | 0,80 | -0,11 | 0,00 | -0,20 | -0,20 | -0,67 | 0,80 | -0,20 | 0,00 | -0,86 | 0,00 | 1,40 |
| m | 0,40 | -0,50 | 1,04 | 0,47 | -0,23 | 0,23 | 3,17 | 0,25 | -0,80 | 0,61 | 0,85 | 2,55 |
| n | 0,05 | -0,18 | 0,56 | -0,73 | -0,83 | 0,50 | 1,50 | -0,30 | -1,05 | 0,14 | 0,20 | 1,05 |
| o | -0,05 | 0,00 | -0,09 | -0,20 | 0,00 | 0,67 | -0,03 | 0,00 | 0,20 | -0,25 | 0,00 | 0,20 |
| p | -0,25 | 0,43 | -0,22 | 0,02 | -0,03 | -0,10 | 0,93 | 0,00 | -0,25 | -0,32 | 0,25 | 0,60 |
| q | -0,05 | 0,00 | 0,36 | -0,78 | 1,50 | 0,77 | 2,00 | 0,00 | 0,60 | 0,04 | 0,25 | 0,20 |
| r | -0,05 | -0,36 | 2,29 | -1,84 | 2,33 | 1,80 | 3,83 | 0,75 | 0,60 | 0,04 | -0,08 | 1,20 |
| s | -0,10 | 0,18 | 1,93 | -0,16 | 0,67 | 2,37 | 0,27 | -0,35 | 0,15 | 0,18 | -0,02 | 0,60 |
| t | 0,00 | 0,00 | 0,11 | -0,18 | 0,67 | 0,67 | 0,00 | 0,05 | 0,00 | -1,75 | 0,00 | 0,00 |
| u | 0,00 | 0,00 | 0,11 | -0,07 | 0,00 | 0,50 | 0,13 | -0,30 | 0,40 | -2,25 | -0,20 | -0,25 |
| v | 1,35 | 0,71 | 2,11 | 0,11 | 1,80 | 1,10 | 1,60 | 1,80 | 1,00 | 0,21 | 0,72 | 0,60 |
| w | 16,55 | 0,79 | 12,18 | 5,38 | -4,40 | 6,63 | 13,37 | 8,85 | 9,45 | 9,00 | 2,10 | 1,50 |
| x | 8,65 | 0,75 | 9,18 | 5,69 | -1,33 | 8,43 | 17,97 | 6,90 | 7,00 | 13,04 | 1,08 | 2,75 |
| y | 1,55 | 0,61 | 2,00 | 1,91 | -1,00 | 3,07 | 3,40 | 1,55 | 0,25 | 4,18 | 1,15 | 1,35 |
| z | 1,15 | 2,00 | 7,31 | 1,89 | -2,73 | 1,47 | 11,27 | 4,75 | -0,55 | 2,82 | 1,70 | 1,20 |
| aa | -0,05 | 1,86 | -0,44 | 0,60 | 0,37 | 0,40 | 1,53 | -0,20 | 0,20 | 0,43 | -0,08 | 0,25 |
| ab | 0,95 | 1,64 | 2,89 | 0,49 | -0,57 | 1,30 | 1,63 | 1,30 | 1,00 | 0,21 | 0,98 | 1,40 |
| ac | 3,05 | 1,04 | 3,80 | 1,91 | 0,73 | -1,20 | 2,73 | 0,50 | 1,15 | 1,11 | -1,05 | -1,30 |
| ad | 2,60 | 0,36 | 1,91 | 0,80 | 1,17 | 2,17 | 1,80 | 1,50 | 0,15 | 0,64 | 1,38 | 3,55 |
| ae | 1,80 | 1,18 | 1,56 | 1,04 | 0,27 | 0,97 | 1,20 | 1,50 | -0,50 | 2,32 | 0,55 | 4,15 |
| af | 1,05 | 2,00 | 2,47 | 0,91 | 0,93 | 1,07 | 2,13 | 2,45 | 0,65 | 1,00 | 0,35 | 3,15 |
| ag | 0,90 | 0,21 | -0,09 | 1,33 | 0,83 | 2,27 | 1,37 | 0,80 | 1,30 | 0,96 | 0,45 | 0,70 |
| ah | 3,20 | -0,96 | 1,36 | 0,24 | 0,07 | 1,30 | 0,27 | -0,10 | -0,30 | 0,71 | 0,55 | 1,00 |
| ai | -0,35 | -1,00 | 1,13 | 0,89 | 0,30 | -0,20 | -0,07 | -1,20 | 0,30 | 0,46 | 0,12 | 0,60 |
| aj | 1,15 | -0,36 | 0,02 | 0,89 | 0,47 | -0,63 | 0,73 | -1,80 | 1,40 | 0,89 | 0,12 | -0,60 |
| ak | 0,55 | -2,50 | -3,84 | -3,18 | 0,33 | -5,90 | -1,20 | -1,30 | 0,35 | -1,61 | -1,92 | -0,05 |
| al | 0,35 | 0,21 | 0,09 | -1,24 | -0,93 | 0,60 | -0,53 | 0,55 | -0,10 | -0,61 | -0,78 | 0,55 |
| am | 5,45 | 4,82 | 7,47 | 1,93 | 14,13 | 8,43 | 28,20 | 8,75 | 5,95 | 7,18 | 4,60 | 5,80 |

**Table 4:** The difference between the average weeks before and after the system's implementation for the nurse's device in the Vaasa hospital PPKL study.

Next, the average week differences for the Rovaniemi and Vaasa PO data sets are presented. The average week differences for the Rovaniemi hospital can be seen in tables 6 and 7. The physician's device lacks data for Sundays, and there is no data for room k in the periods after the system implementation. These values have been removed from the results in the tables. The most frequently visited rooms for the physician's are the rooms *i*, *l*, *q* and *r*. The most frequently visited rooms for the nurse's device are *c*, *p* and *q*. Both devices show similar patterns in which rooms are most visited between normal and on-call time. The clearest difference which can be seen is an increase in the number of visits by the physician's device to rooms *i* and *r*. Room *q*, which is a well-visited room, has strong fluctuations in the amount of visits based on day for both devices. The average weeks for the nurse's phone for the PO study in the Vaasa hospital can be seen in table 8. The data for the physician's phone is not presented here as it appears erratic, with almost all activity being centered to two rooms. Notable differences are the clear decrease in activity for room *r* and the slight increase for room *al*. The fluctuations and differing trends between on-call and normal time for room *z* can also be noted.

| | On-call | | | | | | | Normal | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| room | MON | TUE | WED | THU | FRI | SAT | SUN | MON | TUE | WED | THU | FRI |
| a | 0,00 | 0,57 | 1,52 | -5,96 | -8,88 | 1,42 | 3,15 | -1,37 | 0,50 | 0,05 | 0,58 | -1,40 |
| b | 2,75 | 1,09 | -1,00 | 2,10 | -1,18 | 4,88 | 4,62 | -0,27 | -4,50 | -1,20 | 2,92 | -0,09 |
| c | 13,62 | 3,44 | 0,88 | 0,56 | 9,00 | 8,25 | -1,21 | 4,00 | 1,04 | 4,12 | 1,21 | 3,41 |
| d | -2,45 | 3,18 | -6,65 | -8,73 | -5,43 | -12,20 | -0,85 | 8,68 | 3,35 | 1,05 | -1,75 | -1,37 |
| e | -0,02 | 1,26 | 2,58 | 0,90 | 2,45 | 3,55 | 2,30 | 0,12 | 0,65 | 0,08 | 1,37 | 0,70 |
| f | 0,85 | 1,20 | 0,90 | 0,62 | 0,34 | 1,65 | 1,57 | 0,56 | 0,35 | -0,92 | 0,25 | 1,61 |
| g | 6,42 | 1,57 | 1,65 | -3,90 | 3,50 | 5,18 | -0,82 | -0,38 | 1,31 | -2,30 | -1,80 | -2,69 |
| h | 0,02 | -0,35 | -0,42 | -1,39 | -0,59 | -1,15 | -0,67 | -0,56 | -0,25 | -0,88 | -1,67 | -0,27 |
| i | 0,08 | -0,57 | 0,06 | -0,50 | -0,43 | -0,98 | -0,07 | -0,60 | 0,41 | -0,02 | -1,21 | -0,87 |
| j | 0,85 | 2,91 | 1,58 | 1,35 | 2,62 | 3,10 | 0,33 | 2,03 | 1,41 | -1,58 | 0,92 | 0,79 |
| k | 12,42 | 4,80 | 2,44 | -1,08 | 8,66 | 8,00 | 0,32 | 6,43 | -1,57 | 3,65 | -0,37 | 3,91 |
| l | 2,55 | 0,45 | 0,50 | 0,43 | 0,27 | 1,25 | 1,44 | 0,03 | -0,02 | -2,15 | -0,21 | 0,31 |
| m | -4,55 | -7,02 | -5,44 | -5,75 | -11,07 | 0,52 | -19,89 | -1,28 | -3,39 | -1,98 | -4,63 | -4,44 |
| n | -10,90 | -21,68 | -13,24 | -1,92 | -3,77 | 6,42 | -2,77 | -2,78 | -6,35 | -2,48 | 0,08 | -10,70 |
| o | 56,65 | 75,15 | 67,44 | 67,83 | 67,24 | 133,18 | 80,17 | 10,47 | 19,41 | 11,32 | 18,38 | 21,11 |
| p | -0,05 | -6,62 | -20,60 | -3,19 | 2,89 | -16,38 | -0,52 | 63,31 | 50,02 | 49,12 | 36,67 | 57,40 |
| q | - | - | - | - | - | - | - | - | - | - | - | - |
| r | - | - | - | - | - | - | - | - | - | - | - | - |
| s | 2,55 | 0,18 | 1,47 | -4,31 | 0,64 | 3,10 | -5,17 | -1,74 | 0,43 | -1,62 | -0,20 | -5,07 |
| t | -6,38 | -13,18 | -24,81 | -11,35 | -2,95 | -12,95 | -0,98 | -2,66 | -1,93 | -6,62 | -9,55 | -1,70 |
| u | 4,20 | 1,64 | 1,19 | 1,35 | 2,73 | -0,62 | 0,00 | 49,78 | 40,20 | 46,78 | 43,58 | 47,40 |
| v | -28,40 | -27,11 | -26,56 | -21,24 | -28,64 | -24,32 | -55,39 | -3,98 | -7,29 | -4,68 | -9,70 | -12,36 |
| w | -5,42 | -4,30 | -10,04 | -1,61 | -5,03 | -10,80 | -11,61 | -2,94 | -3,32 | -3,02 | -2,33 | 0,59 |
| x | -0,02 | 0,09 | -1,27 | -5,02 | -0,29 | -1,42 | 0,15 | -0,11 | -0,34 | -2,52 | -1,63 | -0,04 |
| y | 1,60 | 2,15 | 1,63 | 0,23 | 0,98 | 2,12 | 1,80 | 3,73 | 3,61 | -1,05 | 0,46 | 1,89 |
| z | 37,22 | 53,68 | 37,71 | 58,00 | 55,70 | 121,82 | 49,11 | 5,74 | 13,47 | 4,95 | 10,62 | 15,01 |
| aa | -0,60 | 2,34 | 0,42 | 1,96 | -1,56 | 9,70 | 7,97 | -1,72 | -3,79 | -1,72 | 0,83 | 0,00 |
| ab | -0,10 | -0,39 | 0,65 | 0,31 | -1,89 | 3,78 | 1,03 | 0,27 | -0,07 | -1,08 | -0,17 | 0,44 |
| ac | 1,15 | 0,70 | 0,96 | 1,31 | 0,77 | 2,50 | 1,48 | 0,41 | 0,35 | -0,70 | -1,17 | -0,07 |
| ad | -1,72 | 1,26 | -1,89 | -3,67 | -8,85 | -10,42 | -1,03 | 11,00 | 7,77 | 8,98 | 0,33 | 6,61 |
| ae | - | - | - | - | - | - | - | - | - | - | - | - |

**Table 5:** The difference between the average weeks before and after the system's implementation for the nurse's device in the Pori hospital.

| | On-call time | | | | | | | Normal time | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| room | MON | TUE | WED | THU | FRI | SAT | SUN | MON | TUE | WED | THU | FRI |
| a | 0,63 | -0,40 | 0,25 | -0,20 | 0,00 | -0,67 | - | 1,43 | 0,05 | 0,00 | -0,20 | 0,17 |
| b | 0,23 | 4,10 | 2,79 | 2,37 | 2,07 | 2,50 | - | -2,20 | 5,85 | 4,43 | 1,40 | 6,50 |
| c | -1,77 | 0,17 | 2,33 | -2,46 | -3,27 | -7,17 | - | -0,50 | 1,10 | 4,38 | -1,03 | -2,17 |
| d | -0,40 | -0,53 | -0,92 | 1,09 | 0,67 | -1,83 | - | 0,53 | 0,35 | 0,67 | 0,40 | 1,67 |
| e | 0,73 | -1,17 | 0,17 | 0,43 | -2,80 | -1,17 | - | 0,67 | 0,75 | 0,90 | -1,83 | 0,83 |
| f | -0,30 | -0,13 | -0,45 | 0,94 | 0,33 | 0,00 | - | 3,07 | 0,25 | 1,04 | 0,00 | 0,17 |
| g | -1,07 | -0,90 | 3,05 | -2,00 | -1,47 | -6,33 | - | 0,57 | 1,70 | 1,19 | 0,37 | -0,83 |
| h | 2,00 | 4,00 | 1,12 | 1,34 | 1,00 | -1,33 | - | 0,87 | 1,70 | 0,67 | -1,40 | -0,33 |
| i | 32,63 | 36,10 | 34,58 | 34,80 | 20,87 | 3,83 | - | 17,30 | 37,85 | 41,04 | 31,37 | 40,17 |
| j | 0,00 | 0,33 | 0,38 | -0,20 | 0,00 | -0,17 | - | 4,13 | 0,75 | 0,00 | 0,47 | 1,50 |
| k | - | - | - | - | - | - | - | - | - | - | - | - |
| l | 5,43 | 14,50 | 10,08 | 4,17 | 0,67 | -3,67 | - | 6,87 | 9,45 | 8,33 | 2,80 | 7,67 |
| m | 3,30 | 7,00 | 2,95 | -1,11 | 0,93 | -0,67 | - | 5,90 | 2,75 | 6,24 | 1,43 | 2,67 |
| n | -0,07 | 6,97 | 0,25 | 1,60 | -0,20 | 0,83 | - | 1,67 | -1,20 | -1,00 | -0,63 | -0,17 |
| o | 0,20 | 0,90 | -0,17 | 0,86 | 0,13 | -0,33 | - | -0,27 | 0,75 | 1,29 | 0,67 | 1,50 |
| p | -10,73 | -3,77 | 7,75 | 1,97 | -1,53 | -0,50 | - | -2,60 | 5,20 | 7,04 | 5,40 | 3,67 |
| q | -14,07 | -5,13 | 4,67 | 2,43 | 2,07 | -27,17 | - | -5,57 | 12,05 | 17,04 | 1,47 | 3,33 |
| r | 31,83 | 34,30 | 19,71 | 31,89 | 12,53 | 7,50 | - | 11,73 | 22,15 | 25,33 | 21,20 | 30,33 |
| s | 0,93 | 0,57 | 0,12 | 0,20 | -0,20 | -1,50 | - | 1,00 | 0,80 | 0,86 | 0,67 | -0,50 |
| t | -0,67 | 0,57 | -0,21 | -0,29 | 0,33 | 0,50 | - | 5,20 | 0,55 | -0,43 | -0,07 | -0,67 |
| u | 2,17 | -0,17 | -2,21 | 1,00 | -0,87 | -2,67 | - | 2,97 | 2,00 | 1,10 | -0,60 | -0,50 |
| v | 0,00 | -0,43 | -0,67 | -0,60 | 0,00 | 0,00 | - | -1,33 | 0,00 | 0,00 | 0,33 | -0,67 |
| w | 0,57 | 4,20 | 1,42 | 3,03 | 3,13 | -2,00 | - | -2,03 | 2,85 | 4,24 | 1,50 | 5,83 |
| x | 1,77 | 0,50 | 0,25 | 0,37 | 0,00 | -1,00 | - | -0,73 | -0,60 | 0,24 | -0,60 | 3,17 |

**Table 6:** The difference between the average weeks before and after the system's implementation for the physician's device in the Rovaniemi hospital.

| | On-call time | | | | | | | Normal time | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| room | MON | TUE | WED | THU | FRI | SAT | SUN | MON | TUE | WED | THU | FRI |
| a | 0,23 | 1,69 | 1,29 | 3,80 | 1,00 | 2,19 | -1,96 | 1,05 | 1,50 | 2,77 | 3,36 | 0,28 |
| b | -0,50 | 1,63 | 2,91 | -0,31 | -1,17 | -1,90 | -1,07 | 2,12 | 1,83 | 1,50 | 1,74 | -1,14 |
| c | 1,50 | 0,34 | 7,74 | -1,29 | -12,92 | -12,90 | -17,88 | 4,12 | 17,50 | 1,80 | -2,21 | -10,43 |
| d | -0,11 | 0,17 | 0,91 | 0,46 | 0,12 | -0,74 | -0,53 | 0,58 | 1,00 | -0,30 | -0,04 | 0,14 |
| e | 0,95 | -0,20 | 0,63 | 1,20 | -1,29 | -1,36 | -1,79 | 1,38 | 1,16 | -0,30 | 0,43 | -1,57 |
| f | 0,39 | -0,11 | -0,09 | -0,11 | -0,42 | -0,81 | 0,33 | 0,38 | 1,67 | 0,20 | 0,05 | -0,14 |
| g | 2,44 | -1,80 | 0,20 | 0,49 | -2,29 | -5,07 | -6,53 | 2,83 | 1,50 | -1,07 | -8,02 | -3,29 |
| h | -1,11 | 0,11 | 0,40 | 1,31 | -1,21 | 0,31 | 0,79 | 0,25 | 0,00 | 0,20 | 0,36 | 0,15 |
| i | 2,66 | -0,37 | 4,97 | 2,54 | -4,08 | -3,10 | -4,04 | 1,62 | 3,00 | 0,43 | 0,89 | -1,71 |
| j | -0,45 | -0,11 | 0,00 | 0,60 | -1,71 | 0,79 | 0,93 | 0,38 | 0,33 | 0,17 | -0,14 | -0,43 |
| k | - | - | - | - | - | - | - | - | - | - | - | - |
| l | -1,33 | 5,63 | 3,74 | 4,40 | -1,75 | 0,00 | -5,10 | 0,83 | 2,17 | 4,03 | 1,41 | -1,00 |
| m | -0,83 | -0,09 | 2,80 | 0,29 | -3,55 | 0,40 | -1,12 | 2,62 | 0,67 | 3,80 | 0,19 | -1,72 |
| n | 0,28 | -0,03 | -0,09 | 0,26 | -0,38 | 0,38 | -1,12 | 0,38 | 1,00 | 0,50 | 0,02 | 1,00 |
| o | 0,78 | 0,86 | 0,51 | 0,37 | 0,42 | 0,47 | -2,04 | 0,75 | 0,50 | 2,13 | 0,62 | -0,57 |
| p | 0,55 | 5,23 | -1,54 | 1,03 | -12,00 | -0,86 | 27,00 | 4,25 | 2,83 | 3,73 | -4,38 | -6,29 |
| q | 6,34 | 12,83 | 17,29 | 13,91 | -24,25 | -15,03 | -1,97 | 14,62 | 23,33 | 0,03 | 12,33 | -15,14 |
| r | 0,16 | 1,46 | 0,43 | 1,29 | -2,45 | -2,33 | -2,31 | 0,50 | 0,33 | -0,67 | -0,21 | -0,15 |
| s | -0,05 | -0,71 | -0,83 | -0,17 | -2,95 | -0,12 | -1,74 | -1,17 | 1,50 | 1,43 | 0,39 | -2,72 |
| t | 0,22 | -0,26 | -0,20 | 0,51 | -0,25 | 0,19 | 0,33 | -0,12 | 0,17 | -0,43 | 0,12 | -0,43 |
| u | -0,66 | 1,20 | 1,94 | -1,29 | -1,50 | -1,53 | -1,04 | 0,92 | 1,16 | 0,70 | -0,17 | 1,43 |
| v | 0,55 | -0,29 | 1,17 | 2,09 | -3,00 | -0,69 | -3,69 | -1,21 | 1,17 | 1,07 | 1,48 | -3,43 |
| w | 1,89 | -2,60 | 2,17 | -1,49 | -3,21 | -10,67 | -6,76 | 3,33 | 2,00 | -4,53 | 2,89 | -4,28 |
| x | -1,06 | 0,34 | -0,37 | 0,43 | 0,75 | -2,62 | -1,40 | -0,88 | 0,33 | -6,10 | 0,62 | -0,86 |

**Table 7:** The difference between the average weeks before and after the system's implementation for the nurse's device in the Rovaniemi hospital.

| | On-call | | | | | | | Normal | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| room | MON | TUE | WED | THU | FRI | SAT | SUN | MON | TUE | WED | THU | FRI |
| a | 1,00 | -2,05 | -1,98 | -1,93 | -2,08 | 3,60 | -3,30 | 5,33 | 2,04 | 0,51 | 1,50 | -1,75 |
| b | 1,81 | -0,20 | 0,30 | -0,36 | 0,50 | 0,80 | 0,50 | 1,50 | -1,14 | 1,31 | -2,50 | -3,25 |
| c | -3,81 | 1,70 | 6,42 | 0,75 | -2,92 | 16,40 | 0,60 | 5,50 | 8,47 | 9,60 | 6,16 | 3,50 |
| d | -7,57 | 12,10 | 5,08 | 6,86 | 8,58 | 23,07 | -2,90 | 10,67 | 15,90 | 17,60 | 9,84 | 5,50 |
| e | 3,96 | -2,90 | 18,70 | 12,04 | -1,25 | 11,20 | -1,20 | 3,67 | -1,33 | 3,26 | 1,16 | -4,92 |
| f | 10,38 | -0,70 | 9,28 | 12,89 | 7,25 | 0,07 | 2,00 | 1,50 | 0,33 | 0,60 | -0,50 | -4,08 |
| g | 1,29 | 0,25 | 0,15 | -0,25 | -2,00 | 1,73 | 1,90 | -0,33 | 3,81 | 2,29 | -0,17 | 0,67 |
| h | -0,24 | 0,10 | -2,15 | -2,07 | 0,17 | 1,27 | -0,20 | 0,33 | -2,10 | 1,17 | -2,17 | -1,17 |
| i | 0,14 | 0,00 | -0,08 | 0,14 | 0,00 | 1,00 | 0,20 | 0,00 | 0,71 | 0,14 | 0,00 | 0,00 |
| j | -22,90 | -7,80 | -0,20 | 0,00 | 0,75 | 0,00 | 0,00 | -21,50 | -7,76 | -0,06 | 0,34 | 0,33 |
| k | -0,10 | 0,70 | 0,22 | -0,96 | -0,17 | -0,47 | 0,40 | 0,50 | 0,53 | -0,06 | -0,66 | 1,25 |
| l | -1,24 | -1,40 | 0,98 | -0,39 | 0,75 | 1,87 | 0,20 | -2,67 | 1,57 | -0,57 | -2,00 | 1,25 |
| m | 1,00 | 0,35 | -0,28 | -0,86 | 0,08 | 1,93 | 0,30 | 0,16 | 2,04 | 1,11 | -1,50 | 0,67 |
| n | 0,24 | 0,00 | -0,38 | -0,36 | 0,42 | 0,00 | -0,30 | 0,84 | 1,04 | 0,40 | 0,50 | 1,25 |
| o | -1,38 | 0,50 | -24,22 | -9,61 | -0,25 | -1,13 | -0,60 | 0,33 | -0,38 | -10,71 | -1,33 | 0,17 |
| p | -0,96 | 0,90 | 0,85 | -0,07 | -0,33 | 1,33 | 0,40 | -5,67 | 2,38 | 1,26 | 1,50 | 0,00 |
| q | -4,19 | -0,50 | -5,58 | -1,11 | -4,67 | 7,47 | 2,70 | 3,00 | -3,57 | 4,49 | -14,67 | -6,92 |
| r | -20,57 | -29,10 | -15,58 | -25,04 | -27,50 | -4,53 | -23,30 | -9,50 | -22,71 | -6,69 | -19,33 | -17,92 |
| s | -3,29 | -1,50 | 1,32 | -0,75 | -0,67 | 3,73 | -0,10 | -1,66 | 2,04 | 0,40 | 1,66 | -1,17 |
| t | -3,00 | -8,05 | 1,92 | 2,75 | 5,00 | 11,33 | -7,80 | 2,66 | 1,00 | 1,83 | 4,33 | 2,67 |
| u | 4,67 | 3,35 | 9,68 | -4,54 | -5,75 | -22,60 | -26,60 | 8,83 | 8,10 | -2,40 | -0,17 | 9,25 |
| v | -2,57 | 1,00 | 4,82 | 4,64 | -1,00 | 14,33 | -9,50 | 1,17 | 3,00 | 0,71 | 1,50 | 2,25 |
| w | 4,90 | -1,35 | -0,62 | 5,96 | 4,08 | 6,73 | 4,50 | 2,50 | 2,00 | 0,83 | 1,17 | 1,92 |
| x | -6,19 | -1,45 | -1,45 | 3,07 | -2,00 | -5,13 | -0,80 | 0,33 | 1,57 | -0,17 | 1,17 | 0,67 |
| y | 1,00 | -0,40 | -2,05 | -1,43 | -0,17 | -1,13 | -4,90 | 1,67 | 3,38 | -0,94 | 1,83 | -0,33 |
| z | -11,38 | -8,05 | 8,60 | -2,57 | -1,83 | -9,20 | -42,50 | 9,17 | 9,57 | -5,40 | -5,00 | 11,42 |
| aa | 3,10 | -0,45 | 4,55 | -1,96 | 2,00 | -2,27 | -4,60 | 2,17 | 0,81 | 1,34 | 0,17 | -0,42 |
| ab | -0,47 | 0,55 | 1,30 | 2,00 | 0,92 | 0,93 | -7,10 | 0,34 | 0,96 | 0,46 | 0,67 | 0,75 |
| ac | -0,71 | -1,10 | -0,55 | -0,64 | -2,58 | 2,07 | -1,10 | 1,33 | 1,29 | 1,09 | 1,16 | 0,42 |
| ad | -9,86 | -12,25 | -2,98 | -7,89 | -9,50 | 3,27 | -4,90 | -1,66 | -5,47 | 0,60 | -2,50 | -8,58 |
| ae | -0,33 | 0,10 | -0,40 | 0,00 | -0,67 | -0,67 | -0,50 | 0,00 | 0,00 | -0,20 | -0,33 | -0,33 |
| af | -0,67 | -2,45 | -0,35 | -0,75 | -0,42 | 0,67 | -0,70 | 0,00 | 0,24 | 0,14 | -0,17 | 0,17 |
| ag | -1,71 | 1,45 | 0,72 | -0,43 | -1,50 | 2,40 | -2,30 | 1,00 | 0,90 | 1,17 | -0,67 | 0,33 |
| ah | -0,04 | -0,15 | -1,40 | -0,61 | 0,08 | 0,13 | 0,00 | -0,67 | 1,19 | 0,51 | 0,50 | 1,08 |
| ai | -0,19 | -0,40 | -20,95 | -9,00 | 0,25 | -0,27 | -1,00 | -0,16 | 0,38 | -9,40 | 0,17 | 0,92 |
| aj | 0,04 | 0,30 | -0,50 | -1,11 | -2,42 | -0,27 | -1,00 | 0,33 | 1,29 | 0,23 | 0,16 | -1,42 |
| ak | 1,14 | -6,30 | -5,85 | -4,61 | -4,58 | 6,60 | -4,50 | 10,16 | 8,24 | -1,09 | -10,50 | -4,92 |
| al | 1,47 | 10,00 | 0,30 | 4,36 | 0,25 | 18,67 | 4,60 | 4,67 | 3,33 | 13,37 | -2,50 | 9,00 |
| am | -12,86 | -22,45 | 0,62 | 0,57 | 0,50 | 0,60 | -1,20 | 0,67 | -24,04 | 0,23 | -0,16 | 0,25 |

**Table 8:** The difference between the average weeks before and after the system's implementation for the nurse's device in the Vaasa hospital PO study.

## 5.3 Average visit durations

In this section, the differences between the average visit duration models, created for the rooms in each site and for each device, will be presented. The differences are presented as durations in minutes and seconds, with a positive duration indicating an increase in the visit average visit duration from the time before the system's implementation to the time after, and with a negative duration indicating a decrease. When one or both of the periods do not have any visits available for a room, no average can be calculated for that period and thus no difference will be available. This will be indicated with a hyphen in place of the duration.

On the following pages, the differences in average visit durations for the sites will be presented in table format. The results for the nurse's device in the Vaasa hospital's PPKL study, normal and on-call time, are presented in table 9. Strong decreases can be seen for rooms *i*, *n* and *aa* in both normal and on-call time, and for room *al* in on-call time. The differences in the average visit durations for the nurse's device in the Pori hospital, normal and on-call time, can be seen in table 10. A decreasing trend can be seen, without any rooms showing significant changes. The strongest changes are for are rooms *o* and *p* for normal time, and *d* and *f* for on-call time. The differences in the average visit durations for the physician's and nurse's devices in the Rovaniemi hospital, normal and on-call time, can be seen in table 11. The physician's device shows greater decreases in visit durations than the nurse's device. Again, no rooms stand out among the data for either device, with the strongest changes being in room *j* on-call time for the physician's device and in room *d* normal time for the nurse's device. The differences in the average visit durations for the nurse's device in the Vaasa PO study can be seen in table 12. The results for this device show a relatively small difference between the two periods, with most rooms having a duration difference less than a minute. Overall, the durations appear to have a decreasing trend throughout all of the results.

| Nurse's device | | |
|---|---|---|
| room | Normal | On-call |
| a | 00:01 | -01:51 |
| b | -00:18 | -00:33 |
| c | 00:17 | 00:13 |
| d | 00:13 | -00:23 |
| e | 00:54 | -02:45 |
| f | -01:24 | 01:44 |
| g | -02:32 | -03:39 |
| h | -10:02 | 00:00 |
| i | -06:22 | -07:17 |
| j | -01:15 | -02:59 |
| k | 02:55 | -01:17 |
| l | -06:12 | -01:47 |
| m | 02:14 | 00:43 |
| n | -09:26 | -08:12 |
| o | 00:20 | 08:33 |
| p | 00:07 | -00:21 |
| q | -00:22 | -00:23 |
| r | 00:13 | -00:13 |
| s | -01:18 | -01:12 |
| t | -00:14 | -00:24 |
| u | -02:31 | 04:38 |
| v | 02:09 | -03:23 |
| w | -01:17 | -02:32 |
| x | -01:41 | -04:01 |
| y | -04:33 | -00:56 |
| z | -00:50 | 00:11 |
| aa | -11:47 | -05:15 |
| ab | 00:28 | 00:21 |
| ac | -00:50 | -00:25 |
| ad | 03:00 | 05:46 |
| ae | 01:14 | -06:04 |
| af | -01:27 | -04:28 |
| ag | 00:54 | -05:40 |
| ah | 02:23 | -05:15 |
| ai | 01:27 | -02:13 |
| aj | 01:40 | -06:29 |
| ak | -03:23 | -00:10 |
| al | 00:43 | -11:07 |
| am | -02:30 | -01:26 |

**Table 9:** Differences for the average visit durations between the periods before and after the system's implementation, for each room and for the nurse's device in the Vaasa PPKL study. The durations are displayed as minutes and seconds.

| Nurse's device | | |
|---|---|---|
| room | Normal | On-call |
| a | -00:13 | 02:48 |
| b | 00:23 | -00:31 |
| c | -00:40 | -00:54 |
| d | -02:05 | -03:47 |
| e | -01:45 | -00:14 |
| f | 01:34 | -04:25 |
| g | 00:24 | 00:16 |
| h | 00:09 | 00:11 |
| i | -00:31 | 01:22 |
| j | -00:50 | -01:39 |
| k | -01:13 | -00:07 |
| l | -00:55 | 00:10 |
| m | -02:02 | -00:05 |
| n | -01:21 | 00:06 |
| o | -04:01 | -02:01 |
| p | -03:51 | -00:04 |
| q | - | - |
| r | - | - |
| s | 00:30 | -00:58 |
| t | -00:47 | -01:51 |
| u | -01:52 | -00:00 |
| v | -02:34 | -01:58 |
| w | -00:48 | -01:14 |
| x | 01:08 | 02:37 |
| y | -01:37 | -03:22 |
| z | -00:02 | 00:43 |
| aa | 00:19 | -00:16 |
| ab | -01:39 | 00:18 |
| ac | -02:58 | 00:25 |
| ad | -02:21 | -01:53 |
| ae | - | - |

**Table 10:** Differences for the average visit durations between the periods before and after the system's implementation, for each room for the nurse's device in the Pori hospital. The durations are displayed as minutes and seconds.

| | Physician's device | | Nurse's device | |
|---|---|---|---|---|
| room | Normal | On-call | Normal | On-call |
| a | 02:17 | -02:25 | 00:04 | -00:16 |
| b | -00:13 | -01:24 | 00:02 | 00:12 |
| c | -04:03 | -04:05 | -00:56 | -00:42 |
| d | -00:25 | 00:57 | 04:31 | -00:29 |
| e | -02:34 | -03:24 | -00:10 | 00:25 |
| f | -02:36 | -01:44 | -01:15 | -00:40 |
| g | -00:07 | -01:30 | -00:43 | 00:00 |
| h | -00:20 | 00:37 | 00:40 | 00:21 |
| i | -02:21 | -02:17 | -01:54 | 00:43 |
| j | 01:03 | -05:47 | 00:16 | 02:28 |
| k | - | - | - | - |
| l | -01:01 | -02:08 | 00:32 | -00:23 |
| m | -01:57 | -00:56 | 00:24 | 00:07 |
| n | 02:20 | 00:50 | -01:14 | 01:08 |
| o | 03:21 | -00:10 | 02:10 | -01:49 |
| p | -05:10 | -03:20 | -01:14 | -01:07 |
| q | 00:57 | 00:59 | -00:52 | -00:15 |
| r | -00:22 | -00:35 | -01:14 | 00:42 |
| s | 00:09 | -02:47 | -00:10 | -04:17 |
| t | -01:13 | 00:22 | 02:05 | -01:24 |
| u | -03:08 | -00:51 | -03:38 | -00:21 |
| v | 12:14 | -01:52 | -02:45 | -02:30 |
| w | -01:13 | -01:41 | -00:03 | 00:46 |
| x | -02:50 | -03:20 | 00:16 | -01:13 |

**Table 11:** Differences for the average visit durations between the periods before and after the system's implementation, for each room and for both devices in the Rovaniemi hospital. The durations are displayed as minutes and seconds.

| | Nurse's device | |
|---|---|---|
| room | Normal | On-call |
| a | -01:20 | -00:43 |
| b | -00:32 | -01:45 |
| c | 00:21 | 00:06 |
| d | 00:10 | 00:20 |
| e | 00:08 | -00:40 |
| f | -01:17 | -00:40 |
| g | -00:40 | 00:55 |
| h | -01:07 | 00:28 |
| i | - | -00:57 |
| j | 01:56 | -02:35 |
| k | -00:52 | -01:21 |
| l | 00:43 | -03:35 |
| m | -00:09 | 00:23 |
| n | -00:59 | -00:16 |
| o | -00:18 | -00:04 |
| p | 01:38 | -01:20 |
| q | 00:12 | 00:44 |
| r | -00:03 | -00:05 |
| s | 00:27 | -00:47 |
| t | -00:15 | -00:01 |
| u | -00:08 | -00:30 |
| v | -00:38 | 00:33 |
| w | 00:09 | -00:21 |
| x | 00:50 | 00:45 |
| y | -00:10 | 00:01 |
| z | -00:06 | -00:10 |
| aa | 00:24 | -00:34 |
| ab | -01:28 | -01:25 |
| ac | 00:03 | -01:54 |
| ad | 00:59 | 00:06 |
| ae | - | 03:00 |
| af | -01:30 | 01:13 |
| ag | -00:03 | -01:16 |
| ah | -01:13 | -03:13 |
| ai | -04:29 | -03:13 |
| aj | -02:30 | -03:45 |
| ak | 00:33 | -00:14 |
| al | 00:18 | 00:37 |
| am | -00:56 | -01:11 |

**Table 12:** Differences for the average visit durations between the periods before and after the system's implementation, for each room for the nurse's device in the Vaasa PO study. The durations are displayed as minutes and seconds.

# 6 Discussion

## 6.1 Interpretation of the results

When looking at the Markov chain models, patterns can be seen in the data but their meaning and significance is difficult to grasp. One property of the sites which can be obtained from the Markov chains is which rooms are likely to be corridors or other type of central rooms. The room *w* in the Vaasa hospital is an example of this, as it appears to be connected to most other parts of the site. For an analyst this information will hold little value, as this information is already available to them. However, this helps with validating the results if the connections and patterns appear sensible and match the layouts of the sites. The main uses for the results in the Markov chains will likely be to extract percentages for changes which are deemed interesting based on the other results. As an example, the room *r* in the Rovaniemi hospital has received a strong increase in visit counts from the nurse's device, while the sources of the traffic are largely unchanged in the Markov chains. This result may, however, be of higher relevance than other, more visible changes.

The average week models display clear patterns, which often are uniform throughout the week. When looking at how the amount of visits rise sharply in one part of the site and drop sharply in one part of the site, the question of what may be causing such a change arises. The changes in the values for rooms *o*, *v* and *z* in the Pori hospital are an example of such a change. A likely reason which comes to mind is a change in work tasks, requiring the personnel to more frequently visit one part of the site than the other. Identifying such variables affecting the results will be necessary before drawing conclusions about the information system being analyzed. For most rooms, the data for normal time and on-call time appear to display similar trends. When this is not the case, the trend is usually weaker for one of the partitions. In rare cases, an opposite trend can be seen. The rooms *p* and *ad* in the Pori hospital are an example of this. A slight increasing trend in visit counts can be seen across all of the sites.

Overall, the visit durations appear to have become shorter throughout all of the sites and devices which have been analyzed. The interesting thing about this is how clear the decreasing trend is. However, the low amount of visits to some rooms, which can be seen in the average week models, raises concerns about whether the amount of data is sufficient for this type of analysis, even without separating the results into different weekdays. One place where this is evident is in the table for the nurse's device in the Vaasa PO study, which lacks a value for two rooms due to there not being a single visit to these rooms in one of the periods. The best solution during analysis will be to evaluate the results on a room-by-room basis, after the rooms of interest have been identified.

Moreover, the negative trend across the sites and devices is still strong enough to be of relevance. This trend, along with the slight positive trend in visit counts indicate that the tracked entities move around to different parts of the site more in the period after the system's implementation, staying put in one place for shorter durations.

When creating the models, multiple cases of devices having erratic data were encountered. All erratic data in the data set comes from the physicians' devices, with the Rovaniemi hospital's physician's device being the only one with fully valid data. The erratic data displays different properties between the sites, with some showing little to no activity outside a few select rooms, or otherwise unusually small amounts of activity. Speculations as to what may have caused the erratic data are that the devices may have been carried around very little or not at all, that they have malfunctioned somehow during the collection process or that the data has been lost during post-processing. The Vaasa PPKL and Pori physician's devices have valid data for the periods before the system's implementation, while the Vaasa PO study lacks valid data for all periods of the device assigned to the physician, which was switched midway.

To review the goal of the analysis, it is to find a quantifiable result which describes a change which has occurred from taking the new information system in use. While it can be concluded that a notable change has occurred in the activity and mobility patterns of the tracked personnel from the time before the system's implementation to the time after its implementation, this change cannot be attributed to the system based on these results alone. To rule out other factors which may have caused these changes, e.g. new work tasks, an expert analysis with access to domain knowledge for the sites under analysis would have to be performed. The prerequisite for being able to make an assessment of the system's efficiency is to rule out other variables affecting the movement patterns, and to define criteria for measuring the system's efficiency in terms of the movement patterns. As an example, if the system is expected to decrease the number of required in-person visits to the shift leader, this information can be obtained from the created models, provided that the shift leader can be associated with a known location. It is also possible to compress some of the created models into a single value, e.g. the average duration for any visit performed, but this would sacrifice much of the information available in the data set, making extracting values of interest from the created models the preferred method.

## 6.2 Evaluation of the methods

Of the created models, the Markov chains are the ones which provide the least value on their own for an expert analysis. This is due to the large amount of information they contain, and how the least visited rooms are prone to display the largest fluctuations when a difference is calculated. If rooms and paths of interest are known beforehand, however, the usefulness of these models is increased. For rooms of interest, they provide percentages for the outgoing and incoming traffic, which may be a desirable result in this type of analysis. Markov chains are well-researched and are used for numerous purposes, making them an ideal tool for further analysis as well. For a Markov chain model based on indoor positioning data to be useful, it should be based on sufficient amounts of data and the parts of the site should have been somewhat evenly visited in order to avoid states which are absorbing or unreachable, as these do not naturally occur in an indoor environment. One workaround for an uneven distribution of visits is to manually merge less frequently visited parts of the site into fewer states. Most methods utilizing Markov chains also require a starting state to be defined, meaning that sites which do not have a clear entry point for paths, such as the ones in this case study, require rooms of interest to be defined beforehand.

The average week models are the ones which arguably provide the most useful information for this type of analysis. This is due to how they provide a concise overview of the site's activity both spatially and temporally, and how greater fluctuations in activity correlates with the relevance of each room, which is not the case with the other models. They also do not suffer from sparse data or uneven activity across the site, but rather they reveal such properties in the data. The information available in these models also increases the usefulness of the other models, as the amount of visits a room receives provides a measure of the room's relevance and the reliability of information which is dependent on the amount of visits to a room.

The average visit durations function as the most concrete metrics for "efficiency" among the created models, but they have the downside of having a greater dependency on the amount and the quality of data. Due to the high variance among the visit durations, the average visit durations display similar issues to the ones present with the Markov chain models, with less visited rooms being likely to display greater fluctuations. They also depend on a room being visited to calculate an average for that room, while the average amount of visits only requires that the device is active during the day in question. The information contained in this type of model is, however, likely to be useful when performing an expert analysis. A probable goal of the type of system being evaluated here is to increase the time spent per visit in locations where work is performed, while tasks such as fetching equipment should take less time. This information would be easy to extract from these models.

# 7 Conclusion

In this thesis, the field of indoor positioning has been presented and a case study focused on the analysis of movement patterns in indoor tracking data has been performed. The results of the case study showcase examples of models which can be created to compare the differences in the mobility patterns in indoor tracking data sets from the same location, independent of the difference in size between the data sets. The used models were Markov chains, average weekday visit counts and the average visit durations. These were used to model the people flow, activity in different parts of the site and the time spent in these parts of the site, respectively. The approach for modeling the areas where data had been gathered was a symbolic one, using the proximity-based approach for determining entities' positions. After this analysis, there still exists unexploited information in the data, most notably the actual distance which the tracked entities have moved, which could be utilized in a similar manner. This would require the use of coordinate-based positioning rather than the proximity-based approach used here. With the used approach, it would also have been possible to model the same information in different ways, e.g. to focus on counts for transitions instead of visits. However, the methods chosen for this case study provided a variegated overview of the possibilities when comparing this kind of data and the results were deemed to have potential for use in an expert analysis.

The type of analysis performed here is on data which comes from enclosed and controlled environments. Analysis is envisioned to be performed under similar conditions in the future as well, even as positioning technologies are moving towards hybrid infrastructures, with increasing capabilities to cover larger areas. Due to the privacy concerns regarding people tracking data, this type of data is not expected to become available on a large scale. The tracked entities would still be limited in amount and easily differentiable, even as the venues extend beyond the bounds of a single building. However, there is much room for development for this type of analysis, as tracking systems are rarely the end product when an indoor positioning system is developed, and in cases where they are, most of the research is proprietary. When a site is modeled as a graph, tracking data from this site is essentially a large collection of paths with arbitrary start and end nodes, which is a fairly uncommon starting point in graph analysis. In the light of the background research performed for the thesis, it appears the primary commercial interest for direct applications of tracking data has been within analytics for stores or other venues, while academic interest has been focused on analysis of the nature of people flow itself. Prospects for future developments for the use of tracking data include the need for both theoretical and practical frameworks for dealing with the more intricate aspects of tracking data, such as path choices, in a general manner.

# Sammanfattning på svenska

## Inledning

Avhandlingen presenterar inomhuspositionering från ett brett perspektiv genom en överblick över de teknologier, algoritmer och designaspekter som är relevanta vid skapandet av inomhuspositioneringssystem. En fallstudie har även utförts, i vilken inomhuspositioneringsdata som samlats in i en sjukhusmiljö analyseras med målet att evaluera ett informationssystem som tagits i bruk. De data som analyseras är spårningsdata för sjukhuspersonal och avsikten med informationssystemet är att öka deras arbetseffektivitet. Olika metoder för att göra denna typ av analys testas och huruvida denna typ av analys är lämplig för ändamålet evalueras utgående från resultaten.

## Inomhuspositioneringssystem

### Teknologier

Inomhuspositioneringssystem är system som är skapade för att samla in positionsdata i inomhusmiljöer. För detta ändamål är radiobaserade system den populäraste gruppen av teknologier, vilken omfattar teknologier såsom WLAN (eng. wireless local area network) och Bluetooth. Bägge av dessa är teknologier för radiokommunikation på kort distans. WLAN har en räckvidd på 50-100m medan Bluetooth har en räckvidd på 10-15m. Båda teknologierna finns till en stor grad färdigt i infrastrukturen, exempelvis som funktioner i mobiltelefoner, vilket minskar deras implementeringskostnader. Bluetooth kan ses som ett lättare alternativ WLAN och passar för system där energieffektivitet är viktigt. Övriga teknologier för inomhuspositionering inkluderar utomhuspositioneringsteknologier (t.ex. GPS) som anpassats för inomhusbruk, kamerabaserade system eller andra signalbaserade system som använder sig av ljud eller ljus som signaleringsmedium. I radiobaserade och övriga signalbaserade system brukar signalsändarna kallas *fyrar* (eng. beacons), eftersom de utsänder en signal som sedan snappas upp av mottagarna i området.

### Algoritmer

Inom inomhuspositionering används en mängd olika algoritmer för att estimera positionen hos en entitet baserat på sensordata. Signalbaserade positioneringssystem använder sig av modeller för signalspridning för detta. Dessa metoder går ut på att estimera distans eller vinklar mellan fyrarna och mottagarna och sedan beräkna mottagarnas position med denna information eller alternativt genom att direkt använda den närmaste fyrens position som entitetens position. Estimat på distans görs utgående från tiden det tar för fyrens signal att nå till mottagaren och på signalstyrkan när den kommer fram. De olika signaltypernas hastigheter är kända. För att göra dessa estimat finns flera metoder som skiljer sig i t.ex. om signalen skickas fram och tillbaka eller endast en väg. Styrkan på den mottagna signalen kan användas för att uppskatta antalet flervägsfel som uppkommit av hinder i omgivningen. För estimat på vinkel krävs hårdvara som inte finns i de vanligaste radiomottagarna, exempelvis riktade antenner. När entiteternas positioner bestäms enbart utgående från vilken fyr som är närmast kallas det närhetsbaserad positionering. Noggrannheten för denna metod bestäms av hur tätt sensorerna är placerade i omgivningen och lämpar sig därför bäst för kompakta områden eller för fall där positioner i form av koordinater inte är nödvändiga.

### Integritet i inomhuspositioneringssystem

I och med att positioneringssystem blir allt vanligare och täcker allt större områden, blir frågan om integriteten hos de människor som spåras allt viktigare. Detta problem omfattar de grundläggande etiska aspekterna, hur de behandlas i lagstiftningen och hur de implementeras på systemnivå. I en undersökning utförd av Basiri et al. framkommer att personer är mera oroade om sin integritet i fråga om inomhuspositioneringsdata än utomhuspositioneringsdata och att integritetsfrågorna väcker mest oro i fråga om spårningssystem. Lagstiftningen mellan olika länder skiljer sig i hur dessa integritetsfrågor behandlas. I EU:s lagstiftning hör positionsdata till definitionen för personlig data och för att samla in denna typ av data krävs medgivande från den berörda personen. I USA finns ingen lagstiftning specifikt för dataskydd, utan istället finns ett flertal lagar som styr företags affärsverksamhet. Dataöverföringen mellan EU-länder och USA styrs av det s.k. Privacy Shield-avtalet, vilket ger amerikanska företag liknande skyldigheter som europeiska företag när de behandlar EU-medborgares data. Det som görs av systemutvecklarna för att verkställa det som krävs omfattar minimerandet av känsligheten hos de data som samlas in och säkerställandet av att de både lagras och överförs på ett säkert sätt. En teknik för minskandet av känslighetens hos data är att anonymisera identifierbar information, exempelvis MAC-adresser. Säker överföring och lagring av data förverkligas genom kryptering.

## Teori och metoder

### Modellering av inomhusområden

Modeller skapas av inomhusområden i syfte att formellt beskriva området där data samlats in, vilket möjliggör fortsatt analys. Som exempel, om området går att beskriva som en graf så kan grafalgoritmer användas för analys av insamlade data. Modellerna kan grovt delas upp i semantiska och spatiala modeller. De semantiska modellerna beskriver egenskaperna hos de objekt som finns i området och de relationer som finns mellan dem. Denna typ av information används i olika navigationssystem exempelvis för att inkludera landmärken i systemet. De spatiala modellerna delas vidare upp i geometriska och topologiska modeller. De geometriska modellerna beskriver områdets former och struktur och används exempelvis i byggnadsplanering. De topologiska modellerna beskriver de rutter som finns i utrymmet. Detta görs ofta genom grafer, där grafens kanter utgör de rutter som finns i utrymmet och noderna är ändpunkter eller korsningar. Hybrida modeller kombinerar egenskaper från flera av de ovannämnda modellerna och används i fall när egenskaperna hos en typ av modell inte räcker till. Exempelvis kan en topologisk modell inkludera semantisk information, såsom vilken utrustning som finns i ett visst rum.

### Geometriska metoder

Trilateration och triangulering är de geometriska metoder som används för beräkning av position i bl.a. signalbaserade och kamerabaserade system. Bägge metoder kan användas i både två och tre dimensioner. Trilateration går ut på att beräkna positionen på en punkt utgående från referenspunkter, vars positioner och distanser till målpunkten är kända. För detta krävs tre referenspunkter för tvådimensionell trilateration och fyra referenspunkter för den tredimensionella varianten. Runt dessa punkter skapas cirklar eller sfärer (beroende på dimension), vars diameter utgörs av distansen till målpunkten. Positionen för målpunkten fås genom att beräkna skärningspunkten mellan dessa. I de flesta verkliga fall finns ingen gemensam skärningspunkt på grund av att distansestimatens noggrannhet begränsas av mätinstrumenten. I dessa fall estimeras positionen genom att ta medeltalet på de parvisa skärningspunkterna mellan cirklarna eller sfärerna. Triangulering använder sig av information om vinklar istället för distans. Triangulering använder sig av två referenspunkter för den tvådimensionella varianten och tre referenspunkter för den tredimensionella varianten. Denna metod går ut på att beräkna distansen mellan referenspunkterna och målpunkten med hjälp av Pytagoras sats. För detta skapas en rätvinklig triangel som har en sida med känd längd, också kallad baslinjen, baserat på distansen mellan referenspunkterna. Hypotenusan i denna triangel utgörs av linjen mellan en av referenspunkterna och målpunkten. Med hjälp av den mätta vinkeln mellan dessa sidor kan hypotenusans längd bestämmas och målpunktens position fastställas.

### Markovkedjor

En Markovkedja är en grafrepresentation av en Markovprocess, vilket är en typ av stokastisk process. Dessa har fått sitt namn efter den ryske matematikern Andrej Markov. Markovprocesser uppfyller Markovegenskapen, vilket innebär att processens framtida lägen endast är beroende av det nuvarande tillståndet. I en Markovkedja representerar varje nod ett tillstånd processen kan anta och de riktade kanterna i grafen beskriver sannolikheten för att byta från startnodens tillstånd till tillståndet som representeras av målnoden. Kanter från noder till sig själva finns även med i Markovkedjorna. Det finns två typer av Markovprocesser, vilka kallas Markovprocesser i diskret tid och i kontinuerlig tid. Diskret tid innebär att processens tillstånd ändrar stegvis, medan kontinuerlig tid innebär att detta sker med godtyckliga mellanrum. Utöver grafrepresentationen kan en Markovkedja uttryckas som en transitionsmatris. I denna typ av matris utgör raderna processens tillstånd och kolumnerna måltillstånden, dvs. värden i matrisen beskriver sannolikheten att byta från radens tillstånd till kolumnens tillstånd. Varje rad utgör således en distribution, dvs. summan av värden på raden är alltid 1. Markovegenskapen uppfylls av ett stort antal processer i olika sammanhang, vilket gör att Markovkedjor används inom ett brett antal områden, bl.a. för textanalys eller för modellering av biologiska processer.

# Fallstudie

## Översikt

I fallstudien som utförts för avhandlingen undersöks de rörelsemönster som finns i spårningsdata insamlad i sjukhusmiljö. Data för sjukhuspersonal av två olika professioner, läkare och sjukskötare, har insamlats i tre olika sjukhus. Målet med analysen är att testa metoder för att evaluera ett nytt informationssystem (härefter "systemet") på basen av ändringar i rörelsemönstren. Insamlingsprocessen är inte en del av det arbete som gjorts för avhandlingen, men den grundläggande informationen om insamlingsprocessen kommer dock att gås igenom. Data kommer från två studier med liknande upplägg, varav den första benämns PPKL (fin. päivystyspoliklinikka)-studien och den andra benämns PO (fin. päivystysosasto)-studien. PPKL-studien har utförts i sjukhusen i Vasa, Björneborg och Rovaniemi, medan PO-studien endast utförts i Vasa. Data har samlats in i fem perioder för PPKL-studien och i fyra perioder för PO-studien. I PPKL-studien är de två första perioderna före systemets ibruktagande och i PO-studien är den första perioden före systemets ibruktagande. Insamlingsproceduren var upplagd så att Bluetooth Low Energy-fyrar placerades runtom i sjukhusen och som sedan avlästes av telefonerna. Telefonerna var utrustade med Android operativsystemet och för att göra avläsningarna användes Android Beacon Library4-applikationen.

## Förbehandling av data

Före data kan analyseras utförs en förbehandling där överflödig och felaktig data rensas bort, och en mer abstrakt datarepresentation skapas. Den positionsrepresentation som valts är symbolisk, med områden modellerade som en graf där varje nod representerar ett rum. För att bestämma telefonernas position används närhetsbaserad positionering. Avläsningarna som gjorts av en telefon benämns *observationer*. Observationer där inga fyrar kunnat kontaktas benämns tomma observationer och utgör den första typen av överflödig data som rensas bort. Två på varandra följande observationer benämns en *övergång*. Övergångar där båda observationernas position är samma rensas också bort, eftersom detta inte är ett pålitligt mått på tiden spenderat på en viss plats. Istället används de tidsmarkeringar som observationerna har för detta. Områden delas upp i *rum* som består av en eller flera fyrar. Ett *besök* i ett sådant rum är de övergångar som endast rör sig bland de fyrar som hör till detta rum. En *rumsövergång* är två på varandra följande besök. Datamängden delas vidare upp i *sessioner,* där en session definieras som en kedja av besök där telefonen i fråga inte är inaktiv. En telefon anses vara aktiv när tiden mellan observationerna för telefonen inte överstiger 30 minuter och när telefonen byter rum åtminstone en gång på 120 minuter. Sessioner kortare än 5 minuter rensas bort. Utöver detta delas datamängden upp i *jourtid* och *normaltid*. Normaltid är vardagar kl. 8:00 - 15:00 och jourtid är all övrig tid.

## Analysmetoder

För analysen har tre modelleringsmetoder valts för att jämföra perioderna före systemets ibruktagande med perioderna efter, skilt för de olika studierna, sjukhusen, professionerna och tidsuppdelningarna. Modellerna skapas för de olika typer av information som finns i datamängden och de är valda så att de inte är beroende av partitionernas storlek och så att så mycket som möjligt av den information som är av intresse ska kunna utnyttjas. Den information som bedömts att vara intressant är vägval, antalet besök i olika delar av området, tid spenderat i olika delar av området och den egentliga gångdistansen. Den valda representationen för position möjliggör utnyttjandet av alla dessa förutom den egentliga gångdistansen. Modellen som valts för att analysera personalens vägval och personflödet i sjukhusen är Markovkedjor som skapas av området. Modellen som valts för att analysera antalet besök till olika delar av områden är genomsnittliga veckor, bestående av det genomsnittliga antalet besök till områdenas olika rum. Modellen för att analysera tiden spenderat i olika delar av området är de genomsnittliga besökstiderna till olika delar av området.

## Resultat och diskussion

Resultaten för metoderna utgörs av skillnaderna som fås när modellerna för tiden före systemets ibruktdagande subtraheras från tiden efter. Markovkedjorna presenteras i form av skillnader mellan kedjornas transitionsmatriser. Eftersom Markovkedjorna innehåller procentuell information, visar ofta mindre besökta, dvs. mindre relevanta, rum större växlingar. Därför bedöms de fungera bäst för analys i samband med de övriga modellerna. Skillnaderna mellan de genomsnittliga veckorna visar tydligast skillnaden mellan perioderna eftersom de använder sig av de egentliga besöksantalen, vilket gör att växlingarnas storlek också visar rummets relevans. Skillnaden i besökslängd till de olika rummen presenteras inte med veckodagar åtskilt p.g.a. att antalet besök blir för glest till de olika rummen. Enstaka fall av att rum inte fått ett enda besök på endera av perioderna som jämförs och inget medeltal kunnat räknas uppkommer ändå. Ett intressant samband som kan ses utifrån dessa modeller är en svag stigande trend i antalet besök till olika rum utöver alla enheter och en klar sjunkande trend i längden på besöken. Ur resultaten framkommer en tydlig skillnad mellan perioderna före och perioderna efter systemets implementation, men det går dock inte att dra slutsatser om orsakerna till denna skillnad baserat enbart på dessa resultat. Övriga variabler, såsom förändrade arbetsuppgifter, bör uteslutas för att få fram effekten som systemet har åstadkommit. För att utvinna konkreta värden för ökad effektivitet ur resultaten bör de analyseras utgående från systemets syfte, exempelvis om systemet förväntas minska antalet besök till skiftesledaren eller om besök till läkemedelsrummet förväntas gå snabbare, så kan värden för detta fås ur dessa resultat.

## Avslutning

I avhandlingen presenterades fältet inomhuspositionering och en fallstudie med spårningsdata från sjukhus utfördes. Resultaten från fallstudien visar exempel på modeller som kan skapas utgående från spårningsdata, som kan användas för att jämföra olika insamlingsperioder och som inte är beroende av skillnaden i storlek hos datamängderna som jämförs. Medan slutsatser om förändringar som skett i det undersökta området inte kan dras på basen av dessa modeller, kan de användas i en expertanalys för att utvinna konkreta värden på förändringar som anses relevanta. Fältet inomhuspositionering håller på att utvecklas i en riktning där hybrida teknologier för att kombinera positionering utomhus och inomhus blir allt vanligare, vilket möjliggör insamling av data i mycket större skala än tidigare. Trots det förespås spårningsdata för analys att komma från liknande, kontrollerade förhållanden som i denna fallstudie, på grund av de integritetsfrågor som denna typ av data berörs av. Det finns dock mycket rum för utveckling när det gäller analys av spårningsdata. Som exempel, när det undersökta området modelleras som en graf utgör spårningsdata i praktiken en samling färdiga stigar, vilket är en ovanlig startpunkt för denna typ av analys.

# Bibliography

[1] Liu, H.; Darabi, H.; Banerjee, P. & Liu, J., *Survey of Indoor Positioning Techniques and Systems*, IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 2007, 37, 1067 - 1080

[2] Fallah, N.; Apostolopoulos, I.; Bekris, K. & Folmer, E., *Indoor Human Navigation Systems: A Survey*, Interacting with Computers, 2013, 25, 21 - 33

[3] Gu, Y.; Lo, A.; Niemegeers, I., *A Survey of Indoor Positioning Systems for Wireless Personal Networks*, IEEE Communications Surveys & Tutorials, 2009, 11, 13 - 32

[4] Drane, C.; Macnaughtan, M.; Scott, C., *Positioning GSM telephones*, IEEE Communications Magazine, 1998, 36, 46 - 54

[5] Basiri, A.; Lohan, E. S.; Moore, T.; Winstanley, A.; Peltola, P.; Hill, C.; Amirian, P.; Figueiredo e Silva, P.; , *Indoor location based services challenges, requirements and usability of current solutions*, Computer Science Review, 2017, 24, 1 - 12

[6] Shirehjini, A. A. N.; Yassine, A.; Shirmohammade, S., *Equipment Location in Hospitals Using RFID-Based Positioning System*, IEEE Transactions on Information Technology in Biomedicine, 2012, 16, 1058 - 1069

[7] Brena, R. F.; García-Vázquez, J. P.; Galván-Tejada, C.E.; Muñoz-Rodriguez, D.; Vargas-Rozales, C.; Fangmeyer Jr., J., *Evolution of Indoor Positioning Technologies: A Survey*, Journal of Sensors, 2017, 2017, -

[8] Roberts J. F.; Stirling T.; Zufferey J.-C.; Floreano D:, *3-D relative positioning sensor for indoor flying robots*, Autonomous Robots, 2012, 33, 5 - 20

[9] Worboys, M., *Modeling Indoor Space*, Proceedings of the 3rd ACM SIGSPATIAL International Workshop on Indoor Spatial Awareness, ACM, 2011, 1 - 6

[10] Faragher, R.; Harle, R., *An Analysis of the Accuracy of Bluetooth Low Energy for Indoor Positioning Applications*, Proceedings of the 27th International Technical Meeting of The Satellite Division of the Institute of Navigation, ION, 2014, 201 - 210

[11] Chen, L.; Thombre, S.; Järvinen, K.; Lohan, E. S.; Alén-Savikko, A.; Leppäkoski, H.; Bhuiyan, M. Z. H.; Bu-Pasha, S.; Ferrara, G. N.; Honkala, S.; Lindqvist, J.; Ruotsalainen, L.; Korpisaari, P.; Kuusiniemi, H., *Robustness, Security and Privacy in Location-Based Services for Future IoT: A Survey*, IEEE Access, 2017, 5, 8956 - 8977

[12] Schloter, C. P.; Aghajan, H., *Wireless symbolic positioning using support vector machines*, Proceedings of the 2006 international conference on Wireless communications and mobile

computing, ACM, 2006, 1141 - 1146

[13] Wang, Y.; Yang, X.; Zhao, Y.; Liu, Y.; Cuthbert, L, *Bluetooth Positioning using RSSI and Triangulation Methods*, 2013 IEEE 10th Consumer Communications and Networking Conference (CCNC), IEEE, 2013, 837 - 842

[14] Jin, P.; Zhang, L.; Zhao, J.; Yue, L., *Semantics and Modeling of Indoor Moving Objects*, International Journal of Multimedia and Ubiquitous Engineering, 2012, 7, 153 - 158

[15] Mautz, R.; Tilch, S., *Survey of Optical Indoor Positioning Systems*, 2011 International Conference on Indoor Positioning and Indoor Navigation, IEEE, 2011, 1 - 7

[16] Gőzse, I.; Passaro V. M. N. ed., *Optical Indoor Positioning System Based on TFT Technology*, Sensors, 2016, 16, -

[17] Medina, C.; Segura, J. C.; De la Torre, À., *Ultrasound Indoor Positioning System Based on a Low-Power Wireless Sensor Network Providing Sub-Centimeter Accuracy*, Sensors, 2013, 13, 3501 - 3526

[18] Terra, R.; Figueiredo, L.; Barbosa, R.; Anacleto, R., *Traveled Distance Estimation Algorithm for Indoor Localization*, Conference on Electronics, Telecommunications and Computers – CETC 2013, Elsevier / Procedia Technology, 2014, 248 - 255

[19] King, T.; Kopf, S.; Haenselmann, T.; Lubberger, C.; Effelsberg, W., *COMPASS: A Probabilistic Indoor Positioning System Based on 802.11 and Digital Compasses*, Proceedings of the First ACM International Workshop on Wireless Network Testbeds, Experimental Evaluation and Characterization (WiNTECH), ACM, 2006, 34 - 40

[20] Dag, T.; Arsan, T., *Received signal strength based least squares lateration algorithm for indoor localization*, Computers and Electrical Engineering, 2018, 66, 114 - 126

[21] Do, T. M. T.; Dousse, O.; Miettinen, M., *A probabilistic kernel method for human mobility prediction with smartphones*, Pervasive and Mobile Computing, 2015, 20, 13 - 28

[22] Li, B.; Salter, J.; Dempster, A. G.; Rizos, C., *Indoor Positioning Techniques Based on Wireless LAN*, 1st IEEE International Conference on Wireless Broadband and Ultra Wideband Communication, Open Publications of UTS Scholars (OPUS), 2007, -

[23] Crespo, J.; Barber, R.; Mozos, O.M., *Relational Model for Robotic Semantic Navigationin Indoor Environments*, Journal Of Intelligent & Robotic Systems, 2017, 86, 617 - 639

[24] Kim, D.-Y.; Kim, S.-H.; Choi, D.; Jin, S.-H., *Accurate Indoor Proximity Zone Detection Based on Time Window and Frequency with Bluetooth Low Energy*, Procedia Computer Science, 2015, 56, 88 - 95

[25] Dong, Q.; Dargie, W, *Evaluation of the Reliability of RSSI for Indoor Localization*, 2012 International Conference on Wireless Communications in Unusual and Confined Areas, IEEE,

2012, -

[26] Lee, Y.-J.; Mangasarian, O. L., *SSVM: A Smooth Support Vector Machine for Classification*, Computational Optimization and Applications, 2001, 20, 5 - 22

[27] Bekkali, A.; Sanson, H.; Matsumoto, M., *RFID Indoor Positioning based on Probabilistic RFID Map and Kalman Filtering*, Third IEEE International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob 2007), IEEE, 2007, -

[28] Niño-Castañeda, J.; Frías-Velázquez, A.; Bo, N. B.; Slembrouck, M.; Guan, J.; Debard, G.; Vanrumste, B.; Tuytelaars, T.; Philips, W., *Scalable Semi-Automatic Annotation for Multi-Camera Person Tracking*, IEEE Transactions on Image Processing, 2016, 25, 2259 - 2274

[29] Khoselham, K.; Elberink, S. O., *Accuracy and Resolution of Kinect Depth Data for Indoor Mapping Applications*, Sensors, 2012, 12, 1437 - 1454

[30] Gingras, D., *An overview of positioning and data fusion techniques applied to land vehicle navigation systems*, Automotive Informatics and Communicative Systems: Principles in Vehicular Networks and Data Exchange, IGI Global, 2009, 219 - 246

[31] Alessandrini, A.; Gioia, C.; Sermi, F.; Sofos, I.; Tarchi, D.; Vespe, M., *WiFi positioning and Big Data to monitor flows of people on a wide scale*, 2017 European Navigation Conference (ENC), IEEE, 2017, 322 - 328

[32] Meyer, D., *What the GDPR will mean for companies tracking location*, IAPP Privacy Advisor, International Association of Privacy Professionals (IAPP), 2018, https://iapp.org/news/a/what-the-gdpr-will-mean-for-companies-tracking-location/. Accessed on 18. June 2018

[33] Jolly, I., *Data protection in the United States: overview*, Practical Law, Thomson Reuters, 2017, https://uk.practicallaw.thomsonreuters.com/6-502-0467?transitionType=Default&contextData=(sc.Default)&firstPage=true&bhcp=1. Accessed on 18. June 2018

[34] Weiss, M. A.; Archick, K., *U.S.-EU Data Privacy: From Safe Harbor to Privacy Shield*, Congressional Research Service (CRS) Report, Electronic Privacy Information Center (EPIC), 2016, https://epic.org/crs/R44257.pdf. Accessed on 19. June 2018

[35] Zetoony, D. A., *A Side-By-Side Comparison of "Privacy Shield" and the "Safe Harbor": The Easiest Way to Understand What Privacy Shield is and What You Need to Do to Use it*, Practices, Bryan Cave Leighton Paisner LLP, 2016, https://d11m3yrngt251b.cloudfront.net/images/content/8/5/v2/85609/Comparison-of-Privacy-Shield-and-the-Safe-Harbor.pdf. Accessed on 19. June 2018

[36] Jensen, C. S.; Lu, H.; Yang, B., *Graph Model Based Indoor Tracking*, 2009 Tenth International Conference on Mobile Data Management: Systems, Services and Middleware, IEEE, 2009,

122 - 131

[37] Choi, W.; Chao, Y-W.; Pantofaru, C.; Savarese, S., *Understanding Indoor Scenes Using 3D Geometric Phrases*, 2013 IEEE Conference on Computer Vision and Pattern Recognition, IEEE, 2013, 33 - 40

[38] Zhang, J.; Singh, S., *LOAM: Lidar Odometry and Mapping in Real-time*, Robotics: Science and Systems Conference, Robotics Institute, Carnegie Mellon University, 2014, -

[39] Becker, T.; Nagel, C.; Kolbe, T. H., *Supporting Contexts for Indoor Navigationusing a Multilayered Space Model*, 2009 Tenth International Conference on Mobile Data Management: Systems, Services and Middleware, IEEE, 2009, 680 - 685

[40] (no author), *Triangulation*, Britannica Academic, Encyclopædia Britannica, 2018, https://academic-eb-com.ezproxy.vasa.abo.fi/levels/collegiate/article/triangulation/73331. Accessed on 6. May 2018

[41] (no author), *Trilateration*, Britannica Academic, Encyclopædia Britannica, 2018, https://academic-eb-com.ezproxy.vasa.abo.fi/levels/collegiate/article/trilateration/73380. Accessed on 7. May 2018

[42] Wright, J. W.; Lyman, J., *Surveying*, Britannica Academic, Encyclopædia Britannica, 2015, https://academic-eb-com.ezproxy.vasa.abo.fi/levels/collegiate/article/surveying/110295. Accessed on 6. May 2018

[43] Jung, J.; Kim, J.; Yoon, S.; Kim, S.; Cho, H.; Kim, C.; Heo, J., *Bore-Sight Calibration of Multiple Laser Range Finders for Kinematic 3D Laser Scanning Systems*, Sensors, 2015, 15, 10292 - 10314

[44] Brain, M.; Harris, T., *3-D Trilateration*, How GPS Receivers Work, HowStuffWorks.com, 2006, https://electronics.howstuffworks.com/gadgets/travel/gps2.htm. Accessed on 2. July 2018

[45] Norris, J. R., *Markov Chains*. Cambridge University Press, 1997

[46] Graham, C., *Markov Chains: Analytic and Monte Carlo Computations*. Wiley, 2014

[47] Schulz, D.; Fox, D.; Hightower, J., *People Tracking with Anonymous and ID-Sensors Using Rao-Blackwellised Particle Filters*, Proceedings of the Eighteenth International Joint Conference on Artificial Intelligence, IJCAI Organization, 2003, 915 - 920

# Appendix A: Markov chain results

On the following pages, differences in the transition matrices of the Markov chain models created for the case study are presented. These results are covered in section 5.1 of the main text of the thesis.

| Rooms | a | b | c | d | e | f | g | h | i | j | k | l | m | n | o | p | q | r | s | t | u | v | w | x | y | z | aa | ab | ac | ad | ae | af | ag | ah | ai | aj | ak | al | am |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| a | 0,00 | 0,19 | 0,11 | -0,01 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | -0,04 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | -0,06 | 0,00 | -0,02 | 0,02 | 0,01 | 0,00 | 0,01 | 0,00 | 0,00 | 0,01 | 0,01 | 0,00 | 0,00 | -0,02 | -0,01 | -0,00 | -0,15 |
| b | -0,03 | 0,00 | 0,02 | -0,04 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | 0,03 | 0,00 | -0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 |
| c | -0,01 | -0,02 | 0,00 | 0,06 | -0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | 0,01 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | -0,03 | 0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | -0,01 | -0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 |
| d | -0,03 | -0,04 | 0,12 | 0,00 | 0,00 | 0,01 | -0,04 | 0,00 | 0,00 | 0,02 | -0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,02 | 0,01 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,05 |
| e | 0,00 | 0,00 | -0,13 | 0,07 | 0,00 | 0,64 | -0,20 | 0,00 | -0,20 | 0,00 | 0,14 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,33 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| f | -0,03 | 0,00 | 0,02 | 0,03 | 0,08 | 0,00 | 0,14 | 0,00 | -0,01 | -0,12 | 0,03 | 0,00 | 0,01 | 0,00 | 0,00 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,06 | 0,04 | -0,12 | 0,04 | 0,00 | -0,02 | 0,00 | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | 0,00 | 0,00 | -0,04 | -0,04 | -0,02 |
| g | -0,11 | 0,06 | 0,04 | 0,01 | -0,04 | 0,18 | 0,00 | 0,00 | -0,03 | -0,21 | 0,01 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,05 | 0,02 | -0,01 | 0,01 | 0,00 | 0,01 | 0,00 | 0,02 | 0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,01 | 0,01 |
| h | 0,00 | 0,20 | 0,00 | 0,00 | 0,00 | 0,40 | 0,00 | 0,00 | -0,20 | -0,50 | 0,40 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,20 | -0,10 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| i | 0,00 | 0,06 | 0,06 | 0,00 | 0,03 | 0,07 | 0,10 | -0,08 | 0,00 | -0,57 | 0,00 | 0,00 | 0,06 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,07 | -0,03 | 0,00 | 0,03 | 0,00 | 0,06 | 0,00 | 0,06 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,06 |
| j | -0,03 | 0,10 | 0,02 | 0,03 | 0,03 | 0,03 | 0,03 | -0,03 | -0,14 | 0,00 | -0,01 | -0,01 | 0,10 | -0,04 | 0,00 | -0,01 | 0,03 | -0,01 | 0,00 | 0,00 | 0,00 | 0,03 | -0,03 | -0,00 | -0,01 | -0,02 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | -0,01 | -0,01 | 0,00 | 0,00 | 0,00 | -0,03 | -0,02 | -0,01 |
| k | 0,00 | 0,06 | 0,13 | 0,06 | 0,00 | 0,13 | 0,00 | 0,06 | 0,00 | 0,00 | 0,00 | 0,13 | -0,21 | 0,00 | 0,00 | 0,00 | 0,06 | 0,00 | 0,06 | 0,00 | 0,00 | 0,00 | -0,15 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,33 | 0,00 | 0,00 | 0,00 |
| l | 0,00 | 0,00 | -0,20 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,25 | 0,00 | 0,50 | 0,13 | 0,00 | 0,00 | 0,13 | 0,00 | 0,00 | -0,20 | -0,40 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,20 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| m | 0,03 | 0,03 | 0,03 | 0,00 | 0,00 | 0,06 | 0,03 | -0,13 | 0,00 | -0,06 | 0,00 | 0,09 | 0,00 | -0,09 | 0,00 | 0,09 | 0,03 | 0,06 | -0,13 | -0,13 | 0,00 | 0,00 | 0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 |
| n | -0,02 | 0,00 | 0,14 | -0,05 | 0,00 | 0,00 | 0,11 | 0,00 | 0,00 | -0,23 | 0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,05 | -0,03 | 0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,04 | -0,05 | 0,00 | 0,00 | 0,00 | 0,00 | 0,04 | 0,00 | 0,00 | 0,00 | 0,00 |
| o | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,50 | 0,50 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -1,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| p | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,13 | 0,13 | 0,00 | 0,00 | -0,21 | 0,00 | 0,13 | -0,21 | -0,21 | 0,00 | 0,00 | 0,00 | 0,13 | 0,00 | 0,00 | 0,00 | 0,00 | 0,13 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| q | 0,00 | 0,00 | 0,13 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,13 | 0,13 | -0,88 | 0,13 | 0,00 | 0,00 | 0,25 | 0,13 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| r | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,07 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,07 | 0,00 | 0,13 | 0,00 | 0,13 | 0,07 | 0,07 | 0,20 | -0,37 | 0,07 | 0,00 | 0,00 | 0,00 | 0,07 | 0,00 | 0,00 | 0,00 | -0,50 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| s | 0,00 | 0,00 | 0,08 | 0,00 | 0,00 | 0,00 | -0,08 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,08 | 0,00 | 0,00 | -0,08 | 0,17 | 0,00 | 0,00 | -0,17 | 0,00 | 0,33 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,17 | 0,00 | 0,00 | 0,00 | 0,00 | -0,17 | 0,00 | 0,00 | 0,00 |
| t | -0,13 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 1,00 | 0,00 | 0,00 | -0,13 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,13 | 0,00 | 0,00 | -0,25 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,38 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| u | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,07 | 0,00 | -0,07 | 0,00 | 0,50 | 0,00 | 0,00 | 0,00 | 0,25 | 0,25 | -0,13 | 0,00 | 0,00 | -0,13 | 0,00 | -0,07 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,27 | -0,07 | -0,07 | 0,00 | 0,00 | 0,00 | 0,00 | -0,13 |
| v | 0,00 | 0,00 | 0,07 | 0,00 | 0,00 | 0,00 | 0,03 | 0,00 | 0,00 | -0,18 | 0,00 | 0,00 | 0,00 | 0,03 | 0,00 | 0,03 | 0,00 | 0,07 | 0,00 | 0,00 | 0,03 | 0,00 | -0,07 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,20 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 | -0,25 |
| w | -0,02 | 0,02 | 0,02 | 0,02 | 0,00 | 0,01 | -0,02 | -0,00 | -0,02 | -0,12 | -0,00 | 0,00 | 0,01 | -0,03 | 0,00 | 0,00 | 0,00 | 0,01 | 0,01 | 0,00 | -0,01 | 0,03 | 0,00 | 0,01 | 0,02 | -0,01 | 0,00 | 0,05 | 0,01 | 0,03 | -0,00 | -0,00 | 0,00 | 0,03 | -0,01 | -0,00 | -0,07 | -0,01 | 0,04 |
| x | -0,04 | 0,05 | 0,03 | -0,01 | 0,00 | -0,01 | -0,02 | 0,00 | 0,00 | -0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 | 0,00 | 0,06 | 0,00 | -0,01 | 0,00 | -0,10 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | -0,01 | 0,06 |
| y | 0,03 | -0,07 | 0,05 | -0,03 | 0,00 | -0,02 | -0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | -0,05 | 0,12 | 0,00 | 0,03 | 0,00 | 0,00 | -0,06 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 |
| z | -0,05 | 0,07 | -0,02 | 0,05 | 0,00 | 0,03 | -0,02 | 0,00 | 0,00 | -0,03 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | -0,05 | -0,01 | -0,01 | 0,00 | 0,00 | 0,00 | -0,07 | 0,00 | 0,00 | 0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,01 | 0,01 | 0,05 |
| aa | 0,20 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,10 | -0,50 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,10 | 0,00 | 0,10 | 0,20 |
| ab | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,11 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,11 | 0,02 | 0,31 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,04 | 0,02 | -0,11 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| ac | 0,00 | -0,03 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,08 | 0,07 | 0,04 | -0,14 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| ad | 0,02 | 0,00 | -0,08 | 0,00 | 0,00 | -0,08 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,25 | 0,00 | 0,05 | 0,14 | 0,07 | 0,00 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 | 0,31 | 0,11 | 0,00 | -0,08 | 0,00 | 0,00 | -0,07 | -0,08 | -0,07 |
| ae | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | 0,13 | -0,11 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,21 | 0,00 | -0,24 | 0,00 | -0,09 | 0,00 | 0,00 | 0,00 | 0,02 | 0,05 |
| af | 0,01 | 0,03 | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | 0,00 | 0,00 | -0,13 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,06 | 0,00 | -0,09 | 0,00 | 0,05 | -0,02 | 0,00 | 0,00 | 0,00 | -0,04 | 0,00 | -0,01 | 0,16 | 0,00 | 0,00 | 0,05 | 0,01 | 0,01 | 0,01 | 0,04 | 0,00 |
| ag | 0,17 | 0,06 | 0,05 | 0,00 | 0,00 | -0,09 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,06 | 0,00 | 0,00 | 0,00 | -0,04 | 0,05 | 0,02 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,06 | 0,00 | 0,00 | -0,06 | -0,08 |
| ah | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,17 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,05 | 0,31 | 0,00 | 0,00 | 0,05 | 0,00 | 0,00 | 0,00 | 0,05 | -0,17 | 0,32 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,33 | -0,11 |
| ai | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,32 | 0,08 | 0,00 | 0,00 | 0,00 | -0,11 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,08 | 0,00 | 0,23 | 0,08 | 0,08 | -0,11 |
| aj | 0,06 | 0,06 | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,07 | 0,00 | 0,00 | 0,00 | 0,20 | -0,02 | 0,00 | 0,00 | 0,00 | 0,00 | -0,07 | 0,06 | 0,06 | 0,00 | 0,00 | -0,07 | -0,02 | 0,00 | -0,09 | 0,00 | -0,07 |
| ak | 0,01 | 0,10 | 0,03 | 0,00 | 0,00 | 0,00 | -0,03 | 0,00 | 0,00 | -0,13 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 | 0,00 | -0,13 | 0,13 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 | 0,00 | 0,04 | -0,03 | 0,00 | 0,04 | -0,02 | 0,00 | -0,08 | 0,04 |
| al | -0,05 | 0,07 | -0,01 | 0,00 | 0,00 | 0,00 | 0,03 | -0,04 | 0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,04 | 0,00 | 0,00 | 0,00 | 0,00 | -0,04 | 0,00 | -0,08 | 0,00 | 0,00 | 0,05 | -0,05 | 0,00 | 0,00 | 0,00 | 0,00 | 0,06 | 0,06 | 0,00 | 0,00 | 0,00 | -0,19 | 0,00 | 0,19 |
| am | -0,06 | 0,16 | 0,01 | -0,00 | 0,00 | 0,01 | -0,02 | 0,00 | -0,00 | -0,03 | 0,00 | -0,01 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | -0,02 | -0,01 | -0,01 | -0,01 | -0,02 | 0,03 | 0,01 | 0,03 | 0,01 | 0,00 | 0,00 | -0,00 | 0,01 | -0,01 | -0,01 | -0,01 | 0,00 | -0,01 | -0,01 | -0,03 | 0,00 |

**Table 13:** The difference between the Markov chain transition matrices created for the nurse's device in the Vaasa hospital PPKL study for the periods before and after the system's implementation, normal time.

| Rooms | a | b | c | d | e | f | g | h | i | j | k | l | m | n | o | p | q | r | s | t | u | v | w | x | y | z | aa | ab | ac | ad | ae | af | ag | ah | ai | aj | ak | al | am |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| a | 0,00 | 0,11 | 0,04 | 0,00 | 0,00 | -0,01 | -0,01 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,09 | 0,01 | -0,01 | -0,00 | 0,03 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | -0,02 | -0,01 | 0,01 | 0,00 | -0,03 | 0,00 | -0,00 |
| b | 0,01 | 0,00 | 0,06 | -0,01 | 0,00 | 0,00 | -0,00 | 0,00 | 0,00 | -0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,01 | 0,00 | -0,05 | -0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,00 | 0,00 | 0,00 | -0,00 | 0,00 | 0,00 | -0,03 |
| c | -0,02 | 0,03 | 0,00 | 0,01 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | -0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,00 | 0,00 | -0,02 |
| d | 0,01 | -0,04 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 | 0,00 | -0,02 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,01 |
| e | 0,00 | 0,00 | -0,39 | 0,04 | 0,00 | 0,10 | 0,07 | 0,04 | 0,00 | 0,00 | 0,07 | 0,00 | 0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,08 | 0,04 | 0,00 | 0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,13 | 0,00 |
| f | -0,08 | 0,05 | 0,05 | 0,00 | 0,05 | 0,00 | -0,24 | 0,02 | -0,03 | -0,08 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,04 | 0,00 | 0,00 | 0,20 | 0,03 | 0,03 | 0,02 | 0,00 | -0,04 | 0,00 | 0,00 | 0,00 | 0,02 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 |
| g | -0,02 | 0,01 | 0,05 | -0,00 | 0,01 | -0,14 | 0,00 | 0,01 | -0,02 | -0,18 | 0,00 | 0,00 | 0,01 | 0,01 | 0,00 | 0,01 | 0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,01 | 0,18 | 0,01 | 0,02 | 0,05 | 0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,00 | 0,01 | -0,06 |
| h | 0,00 | 0,00 | 0,11 | 0,00 | 0,00 | 0,06 | 0,00 | 0,00 | 0,17 | -0,43 | 0,06 | -0,14 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,06 | 0,00 | 0,00 | 0,00 | 0,00 | 0,10 | 0,00 | 0,06 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,07 | 0,00 | 0,00 | 0,00 | 0,04 |
| i | -0,03 | 0,00 | 0,02 | 0,00 | 0,05 | 0,03 | 0,09 | 0,02 | 0,00 | -0,32 | 0,02 | 0,00 | 0,04 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,08 | 0,04 | 0,00 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 |
| j | 0,01 | 0,01 | 0,07 | 0,04 | -0,00 | 0,01 | 0,02 | -0,05 | -0,03 | 0,00 | 0,00 | 0,00 | 0,01 | -0,12 | 0,00 | 0,00 | -0,01 | 0,01 | 0,03 | 0,00 | 0,00 | 0,00 | -0,04 | 0,04 | 0,00 | 0,01 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | -0,02 | 0,00 | -0,01 |
| k | 0,00 | 0,03 | 0,04 | 0,00 | -0,12 | 0,03 | 0,03 | 0,00 | -0,40 | 0,00 | 0,00 | -0,12 | 0,08 | 0,00 | 0,00 | 0,03 | 0,11 | 0,05 | 0,00 | 0,08 | 0,00 | 0,03 | 0,11 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 | 0,00 | 0,03 |
| l | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,22 | 0,08 | -0,11 | 0,20 | 0,00 | 0,09 | 0,04 | 0,00 | -0,03 | 0,08 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,11 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| m | 0,00 | 0,00 | 0,04 | 0,02 | 0,00 | -0,05 | -0,11 | 0,00 | 0,04 | 0,00 | 0,08 | -0,12 | 0,00 | 0,02 | 0,04 | -0,03 | 0,02 | 0,00 | 0,02 | 0,00 | 0,02 | -0,05 | 0,06 | 0,00 | 0,04 | -0,05 | 0,02 | -0,07 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | 0,02 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 |
| n | -0,03 | 0,00 | -0,01 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | -0,32 | -0,01 | -0,01 | 0,13 | 0,00 | 0,00 | 0,02 | 0,02 | 0,05 | -0,03 | 0,00 | 0,00 | -0,03 | -0,01 | 0,03 | 0,02 | 0,05 | 0,00 | 0,02 | 0,00 | 0,02 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | 0,00 | 0,02 |
| o | 0,14 | 0,29 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,11 | 0,00 | 0,00 | -0,21 | 0,00 | 0,00 | -0,11 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| p | 0,00 | 0,00 | 0,00 | 0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,04 | 0,00 | 0,08 | -0,04 | 0,17 | -0,13 | -0,17 | 0,00 | -0,08 | -0,04 | 0,00 | 0,00 | 0,00 | 0,08 | -0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,08 |
| q | 0,00 | 0,03 | 0,03 | 0,00 | 0,00 | 0,00 | 0,03 | 0,00 | 0,00 | 0,00 | 0,03 | 0,00 | 0,00 | 0,03 | 0,00 | 0,00 | 0,00 | -0,14 | 0,06 | 0,03 | 0,00 | 0,00 | -0,08 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| r | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,04 | 0,00 | 0,00 | -0,03 | 0,01 | 0,06 | 0,00 | -0,03 | 0,00 | -0,03 | -0,04 | 0,03 | 0,00 | 0,11 | 0,02 | -0,06 | 0,03 | 0,02 | 0,01 | 0,01 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | -0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 |
| s | 0,00 | 0,02 | -0,07 | 0,00 | 0,00 | 0,00 | 0,04 | 0,00 | 0,00 | -0,14 | 0,00 | 0,00 | -0,05 | -0,05 | 0,00 | 0,00 | -0,05 | -0,04 | 0,00 | 0,07 | 0,00 | 0,09 | 0,03 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 | 0,02 | 0,05 | 0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,05 |
| t | 0,00 | 0,00 | 0,09 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,09 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,09 | -0,73 | 0,27 | 0,00 | 0,00 | 0,09 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,09 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| u | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,11 | 0,00 | 0,00 | 0,00 | 0,00 | 0,33 | 0,11 | -0,33 | 0,00 | 0,11 | 0,11 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,44 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| v | 0,01 | -0,07 | 0,00 | 0,01 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,01 | -0,02 | 0,00 | 0,00 | 0,00 | -0,11 | -0,05 | 0,00 | -0,05 | 0,00 | -0,15 | 0,01 | 0,00 | 0,02 | 0,00 | 0,04 | 0,00 | 0,26 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 |
| w | -0,01 | 0,04 | 0,03 | 0,01 | 0,01 | 0,01 | 0,02 | -0,00 | -0,00 | -0,06 | -0,00 | -0,00 | 0,01 | -0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,01 | 0,00 | -0,00 | 0,01 | 0,02 | -0,00 | 0,02 | 0,01 | 0,02 | 0,02 | 0,00 | -0,00 | 0,01 | -0,00 | 0,01 | -0,19 | -0,01 | 0,01 |
| x | -0,01 | 0,04 | 0,01 | -0,00 | -0,01 | -0,00 | -0,00 | 0,00 | 0,00 | -0,02 | 0,01 | 0,00 | -0,01 | -0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,07 | 0,00 | -0,02 | 0,03 | -0,01 | 0,00 | 0,01 | 0,00 | -0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,04 |
| y | -0,01 | 0,04 | 0,01 | 0,02 | 0,01 | 0,03 | 0,02 | 0,00 | 0,00 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,02 | 0,00 | 0,00 | 0,01 | 0,01 | -0,01 | -0,13 | 0,00 | -0,01 | 0,00 | 0,01 | -0,05 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 | 0,01 | 0,01 | 0,01 | 0,05 |
| z | 0,02 | -0,10 | 0,04 | 0,03 | 0,00 | -0,01 | 0,01 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | -0,01 | 0,00 | 0,00 | -0,02 | 0,00 | 0,00 | 0,01 | 0,12 | -0,08 | 0,01 | 0,00 | 0,01 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 |
| aa | 0,22 | 0,02 | 0,02 | 0,02 | 0,00 | 0,00 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,14 | 0,06 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | -0,31 | 0,10 |
| ab | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | 0,03 | -0,09 | 0,02 | -0,02 | 0,03 | 0,00 | 0,00 | 0,00 | 0,01 | 0,01 | -0,01 | 0,00 | 0,00 | 0,00 | 0,01 | -0,03 | 0,00 | 0,01 |
| ac | 0,00 | -0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | 0,15 | -0,06 | -0,04 | 0,00 | -0,02 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,02 | -0,02 |
| ad | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,20 | 0,00 | 0,03 | 0,00 | 0,00 | 0,25 | 0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,06 | 0,00 | 0,00 | 0,01 | -0,12 | 0,00 | -0,17 | 0,03 | 0,04 | 0,01 | 0,00 | 0,01 |
| ae | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | -0,07 | 0,01 | 0,01 | 0,00 | 0,00 | 0,03 |
| af | -0,05 | 0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 | -0,04 | 0,00 | 0,02 | -0,07 | 0,02 | -0,01 | 0,03 | 0,01 | 0,01 | 0,00 | 0,00 | 0,04 | 0,04 | 0,00 | 0,00 | 0,03 | 0,01 | 0,01 | 0,01 | -0,03 | 0,02 |
| ag | -0,10 | 0,03 | 0,04 | 0,00 | 0,00 | -0,03 | 0,01 | 0,00 | 0,01 | 0,00 | -0,01 | 0,00 | 0,00 | 0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | 0,01 | -0,03 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | 0,04 |
| ah | 0,02 | 0,00 | -0,08 | 0,00 | 0,00 | 0,00 | -0,08 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,16 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,08 | -0,00 | 0,02 | 0,00 | 0,00 | 0,11 | 0,02 | 0,06 | 0,00 | 0,00 |
| ai | 0,03 | 0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,06 | 0,00 | 0,00 | 0,00 | 0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | -0,06 | 0,00 | 0,00 | 0,00 | -0,03 | 0,00 | 0,03 | -0,03 | 0,00 | 0,00 | 0,18 | 0,00 | -0,20 | 0,09 | -0,06 | 0,03 |
| aj | 0,00 | 0,03 | 0,00 | 0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,08 | 0,05 | 0,00 | 0,00 | 0,00 | 0,03 | 0,00 | 0,08 | 0,03 | 0,03 | 0,00 | 0,00 | -0,21 | 0,00 | -0,11 | 0,03 | -0,03 |
| ak | -0,02 | 0,06 | 0,00 | 0,01 | 0,01 | 0,00 | -0,01 | 0,00 | 0,00 | -0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,25 | 0,04 | 0,00 | 0,01 | 0,01 | 0,01 | 0,01 | 0,02 | 0,00 | 0,10 | 0,00 | 0,00 | 0,01 | 0,01 | 0,00 | -0,01 | 0,01 |
| al | 0,10 | 0,01 | 0,03 | 0,02 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,14 | 0,06 | 0,02 | -0,02 | -0,06 | 0,00 | -0,03 | 0,00 | 0,00 | 0,04 | 0,01 | 0,00 | 0,00 | 0,00 | -0,13 | 0,00 | 0,08 |
| am | -0,04 | 0,05 | -0,03 | 0,01 | 0,00 | 0,00 | -0,00 | 0,00 | 0,00 | -0,00 | 0,00 | 0,00 | -0,00 | -0,01 | 0,00 | -0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,00 | 0,02 | 0,05 | 0,01 | -0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | -0,02 | 0,00 | -0,00 | 0,00 | -0,02 | -0,04 | 0,00 |

**Table 14:** The difference between the Markov chain transition matrices created for the nurse's device in the Vaasa hospital PPKL study for the periods before and after the system's implementation, on-call time.

| Rooms | a | b | c | d | e | f | g | h | i | j | k | l | m | n | o | p | q | r | s | t | u | v | w | x | y | z | aa | ab | ac | ad | ae |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| a | 0,00 | -0,03 | 0,00 | 0,06 | 0,00 | -0,03 | -0,02 | 0,00 | -0,03 | 0,00 | -0,03 | 0,03 | 0,03 | -0,09 | 0,31 | 0,03 | -0,03 | 0,00 | -0,17 | 0,00 | 0,03 | -0,03 | 0,00 | 0,00 | -0,03 | 0,09 | -0,03 | 0,00 | 0,00 | -0,03 | -0,06 |
| b | 0,01 | 0,00 | 0,04 | 0,02 | 0,03 | 0,01 | 0,02 | -0,04 | 0,01 | 0,01 | 0,10 | 0,03 | 0,01 | -0,03 | 0,15 | 0,01 | 0,00 | -0,02 | 0,01 | 0,00 | -0,01 | -0,13 | 0,03 | 0,00 | 0,02 | 0,03 | -0,35 | 0,03 | 0,00 | 0,00 | -0,01 |
| c | -0,03 | -0,03 | 0,00 | 0,02 | 0,01 | 0,00 | -0,01 | 0,00 | 0,00 | 0,02 | -0,07 | 0,01 | -0,01 | -0,04 | 0,08 | 0,06 | -0,01 | -0,05 | 0,00 | 0,01 | 0,02 | -0,01 | -0,01 | 0,00 | 0,04 | 0,02 | -0,00 | 0,01 | 0,01 | 0,00 | -0,04 |
| d | -0,01 | 0,02 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | -0,00 | 0,00 | 0,00 | 0,40 | -0,17 | -0,06 | 0,01 | -0,19 | 0,13 | 0,01 | 0,00 | -0,02 | 0,05 | 0,00 | 0,00 | 0,00 | 0,00 | -0,20 | -0,02 |
| e | -0,03 | -0,08 | 0,04 | 0,07 | 0,00 | 0,01 | -0,07 | 0,00 | -0,03 | 0,00 | 0,05 | 0,00 | 0,01 | -0,02 | 0,06 | 0,08 | 0,00 | -0,03 | -0,04 | -0,06 | 0,04 | -0,13 | 0,00 | 0,01 | 0,04 | 0,03 | 0,06 | 0,00 | 0,00 | 0,03 | -0,03 |
| f | -0,04 | 0,00 | 0,04 | 0,04 | 0,00 | 0,00 | 0,14 | 0,00 | 0,00 | 0,00 | 0,00 | -0,39 | 0,02 | 0,00 | 0,08 | 0,08 | 0,00 | 0,00 | 0,12 | 0,00 | 0,00 | -0,07 | 0,02 | 0,00 | 0,04 | 0,00 | 0,02 | -0,10 | 0,04 | -0,02 | -0,04 |
| g | -0,01 | 0,01 | 0,00 | 0,06 | 0,01 | 0,03 | 0,00 | -0,05 | -0,08 | 0,03 | 0,02 | 0,00 | -0,01 | 0,01 | 0,12 | 0,02 | 0,00 | -0,02 | -0,21 | 0,00 | 0,01 | -0,03 | 0,01 | 0,00 | 0,04 | -0,01 | 0,05 | 0,02 | -0,02 | 0,00 | -0,01 |
| h | 0,00 | -0,12 | 0,00 | 0,00 | 0,17 | -0,06 | -0,08 | 0,00 | 0,47 | 0,00 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,11 | 0,00 | 0,00 | -0,09 | -0,09 | 0,00 | 0,00 | -0,03 | -0,21 | -0,03 | 0,00 | 0,00 | 0,00 |
| i | 0,00 | -0,03 | 0,04 | 0,00 | 0,00 | 0,08 | -0,09 | 0,05 | 0,00 | 0,00 | -0,03 | -0,05 | -0,03 | -0,03 | 0,04 | 0,00 | 0,00 | 0,00 | -0,14 | 0,00 | 0,00 | 0,00 | 0,20 | 0,00 | 0,00 | 0,04 | -0,05 | 0,01 | 0,00 | 0,00 | -0,03 |
| j | -0,01 | 0,01 | 0,04 | 0,06 | 0,02 | 0,02 | -0,02 | 0,00 | -0,01 | 0,00 | 0,02 | 0,01 | -0,02 | -0,06 | 0,11 | 0,10 | -0,07 | -0,04 | -0,07 | -0,05 | 0,04 | -0,01 | 0,00 | -0,01 | 0,10 | -0,05 | 0,00 | 0,00 | -0,01 | -0,01 | -0,03 |
| k | -0,01 | 0,04 | 0,06 | 0,03 | 0,00 | 0,00 | 0,00 | -0,00 | 0,00 | 0,01 | 0,00 | 0,01 | -0,01 | -0,04 | 0,07 | 0,04 | 0,00 | -0,09 | 0,00 | -0,00 | 0,02 | -0,03 | -0,17 | 0,00 | 0,02 | 0,01 | 0,01 | 0,01 | 0,01 | 0,01 | -0,01 |
| l | 0,03 | 0,07 | 0,04 | 0,00 | 0,03 | -0,09 | 0,04 | -0,06 | -0,03 | 0,00 | 0,10 | 0,00 | 0,00 | 0,00 | 0,07 | 0,07 | -0,03 | -0,09 | -0,03 | 0,00 | 0,00 | -0,06 | 0,03 | 0,00 | 0,07 | 0,03 | 0,00 | -0,22 | 0,01 | 0,00 | 0,00 |
| m | 0,02 | 0,03 | -0,00 | 0,00 | 0,08 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 | 0,01 | 0,00 | 0,00 | -0,04 | 0,22 | 0,07 | -0,01 | -0,02 | -0,01 | -0,01 | 0,14 | -0,52 | -0,03 | 0,03 | 0,05 | -0,01 | -0,01 | -0,01 | 0,00 | -0,01 | 0,00 |
| n | 0,01 | -0,02 | 0,04 | 0,01 | 0,00 | 0,00 | 0,00 | -0,01 | 0,01 | -0,02 | 0,02 | 0,00 | -0,03 | 0,00 | 0,00 | -0,02 | -0,01 | -0,05 | -0,01 | -0,01 | 0,01 | -0,25 | -0,08 | 0,00 | -0,01 | 0,46 | 0,02 | -0,01 | -0,01 | 0,00 | -0,05 |
| o | 0,01 | 0,02 | 0,03 | -0,10 | 0,02 | 0,00 | -0,05 | 0,00 | 0,00 | -0,04 | 0,06 | 0,00 | 0,00 | -0,17 | 0,00 | 0,02 | -0,17 | -0,11 | -0,05 | -0,05 | 0,00 | 0,02 | 0,00 | 0,00 | 0,01 | 0,73 | 0,02 | 0,00 | -0,16 | -0,05 | 0,00 |
| p | 0,00 | -0,00 | 0,00 | -0,07 | 0,00 | 0,00 | -0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | -0,01 | -0,00 | -0,00 | 0,00 | -0,05 | -0,32 | 0,00 | -0,38 | 0,73 | -0,00 | 0,00 | -0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,12 | -0,01 |
| q | 0,00 | -0,01 | -0,01 | -0,22 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,05 | -0,02 | 0,00 | -0,01 | -0,01 | -0,02 | -0,08 | 0,00 | -0,08 | -0,01 | -0,14 | 0,00 | -0,01 | 0,00 | -0,07 | -0,21 | 0,00 | 0,00 | 0,00 | -0,01 | -0,02 | -0,02 |
| r | -0,01 | -0,02 | -0,02 | -0,03 | -0,01 | 0,00 | -0,02 | 0,00 | 0,00 | -0,02 | -0,04 | 0,00 | -0,02 | -0,01 | 0,00 | -0,38 | -0,06 | 0,00 | -0,01 | -0,08 | -0,01 | -0,05 | -0,02 | 0,00 | -0,03 | 0,00 | -0,01 | 0,00 | -0,02 | -0,07 | -0,05 |
| s | -0,02 | 0,03 | 0,00 | 0,03 | -0,06 | 0,02 | -0,18 | -0,02 | -0,05 | 0,02 | 0,03 | -0,01 | 0,01 | -0,02 | 0,07 | 0,08 | 0,00 | -0,02 | 0,00 | 0,01 | 0,07 | -0,03 | 0,01 | -0,01 | 0,04 | 0,03 | 0,02 | -0,00 | -0,04 | -0,01 | -0,02 |
| t | 0,00 | 0,00 | 0,01 | -0,05 | 0,00 | -0,00 | -0,02 | 0,00 | 0,00 | 0,02 | 0,00 | -0,00 | 0,00 | -0,01 | 0,01 | 0,22 | -0,08 | -0,06 | -0,00 | 0,00 | 0,12 | -0,00 | 0,00 | -0,05 | -0,00 | 0,00 | 0,02 | 0,00 | -0,00 | -0,09 | -0,02 |
| u | 0,00 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,91 | 0,00 | -0,58 | 0,00 | 0,01 | 0,00 | -0,08 | 0,00 | 0,00 | 0,01 | -0,08 | 0,00 | 0,00 | 0,00 | -0,22 | 0,00 |
| v | 0,01 | 0,03 | 0,05 | 0,04 | 0,01 | -0,00 | 0,01 | -0,01 | 0,01 | 0,05 | 0,17 | -0,01 | -0,20 | -0,18 | 0,17 | 0,06 | 0,00 | -0,04 | -0,00 | 0,00 | 0,02 | 0,00 | 0,01 | 0,00 | 0,04 | -0,16 | -0,05 | 0,02 | -0,01 | 0,01 | -0,03 |
| w | 0,00 | 0,09 | 0,02 | 0,05 | 0,00 | 0,03 | 0,02 | 0,02 | 0,07 | 0,02 | -0,14 | 0,00 | -0,06 | -0,14 | 0,10 | -0,01 | 0,00 | -0,02 | 0,02 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,18 | 0,08 | 0,05 | 0,00 | 0,00 | -0,02 |
| x | 0,00 | 0,00 | 0,00 | -0,17 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,17 | 0,33 | 0,00 | 0,00 | 0,40 | -0,29 | -0,02 | 0,00 | -0,27 | -0,05 | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | 0,00 | 0,00 | 0,00 | -0,07 | 0,00 |
| y | 0,00 | 0,03 | 0,09 | -0,02 | 0,02 | -0,02 | 0,01 | 0,00 | 0,00 | 0,04 | 0,06 | -0,01 | 0,00 | 0,00 | 0,05 | 0,26 | -0,45 | -0,09 | 0,05 | -0,04 | 0,05 | 0,03 | 0,01 | -0,02 | 0,00 | 0,02 | 0,02 | -0,02 | 0,00 | 0,00 | -0,06 |
| z | -0,01 | -0,00 | -0,02 | -0,00 | -0,00 | 0,00 | -0,01 | 0,00 | 0,00 | -0,02 | 0,01 | 0,00 | -0,17 | -0,07 | 0,84 | 0,00 | 0,00 | -0,01 | -0,00 | 0,00 | 0,00 | -0,44 | -0,10 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | 0,01 | 0,00 | -0,01 |
| aa | 0,00 | -0,20 | 0,02 | 0,02 | 0,03 | 0,01 | 0,05 | -0,02 | -0,02 | 0,06 | 0,03 | 0,02 | 0,00 | -0,04 | 0,14 | 0,00 | 0,00 | -0,01 | -0,05 | 0,00 | 0,00 | -0,15 | 0,07 | 0,00 | 0,03 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 |
| ab | 0,00 | 0,05 | -0,00 | 0,03 | 0,03 | 0,16 | -0,03 | -0,07 | 0,06 | 0,00 | 0,05 | -0,28 | 0,00 | -0,04 | 0,06 | 0,06 | 0,00 | -0,03 | -0,07 | 0,03 | 0,00 | 0,02 | 0,03 | 0,00 | 0,03 | 0,00 | -0,10 | 0,00 | 0,00 | 0,03 | 0,00 |
| ac | 0,00 | 0,00 | 0,07 | 0,10 | 0,00 | -0,03 | 0,00 | 0,00 | -0,07 | 0,00 | 0,38 | -0,21 | 0,00 | 0,00 | 0,28 | -0,07 | -0,07 | -0,07 | -0,21 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 | 0,00 | -0,03 | 0,00 | -0,03 | -0,03 |
| ad | -0,01 | 0,00 | 0,00 | -0,36 | 0,00 | -0,01 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | 0,00 | 0,73 | -0,03 | -0,12 | -0,02 | -0,25 | 0,13 | 0,00 | 0,00 | -0,04 | 0,00 | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | -0,01 |
| ae | -0,03 | -0,01 | -0,05 | 0,00 | -0,04 | 0,00 | -0,01 | 0,00 | 0,00 | -0,05 | 0,00 | 0,00 | -0,01 | -0,09 | -0,03 | -0,07 | -0,01 | -0,25 | -0,07 | -0,04 | 0,00 | -0,09 | 0,00 | 0,00 | -0,03 | -0,04 | -0,03 | 0,00 | -0,01 | -0,04 | 0,00 |

**Table 15:** The difference between the Markov chain transition matrices created for the nurse's device in the Pori hospital for the periods before and after the system's implementation, normal time.

| Rooms | a | b | c | d | e | f | g | h | i | j | k | l | m | n | o | p | q | r | s | t | u | v | w | x | y | z | aa | ab | ac | ad | ae |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| a | 0,00 | 0,00 | 0,02 | 0,00 | 0,04 | 0,00 | 0,06 | 0,00 | 0,00 | -0,00 | -0,00 | 0,01 | -0,02 | -0,20 | 0,52 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,09 | -0,05 | 0,00 | -0,01 | -0,33 | 0,05 | 0,00 | 0,01 | 0,00 | -0,01 |
| b | -0,00 | 0,00 | -0,00 | 0,00 | -0,00 | 0,00 | 0,02 | -0,03 | 0,00 | 0,00 | 0,01 | 0,06 | -0,00 | -0,04 | 0,18 | 0,00 | 0,00 | 0,00 | -0,00 | -0,00 | 0,00 | -0,21 | 0,10 | 0,00 | 0,00 | 0,01 | -0,11 | -0,00 | 0,02 | 0,00 | 0,00 |
| c | 0,00 | -0,00 | 0,00 | 0,00 | 0,00 | 0,01 | -0,00 | 0,00 | 0,00 | 0,01 | -0,07 | -0,00 | 0,00 | -0,05 | 0,14 | -0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | -0,07 | -0,01 | 0,00 | 0,00 | 0,04 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 |
| d | 0,01 | 0,01 | 0,02 | 0,00 | 0,01 | 0,00 | 0,01 | 0,00 | 0,00 | 0,13 | 0,03 | 0,01 | 0,03 | 0,02 | 0,11 | -0,16 | -0,08 | -0,02 | 0,00 | -0,02 | 0,00 | 0,02 | 0,00 | -0,03 | 0,07 | 0,03 | 0,00 | 0,00 | 0,00 | -0,18 | -0,01 |
| e | 0,00 | -0,00 | 0,01 | 0,02 | 0,00 | -0,01 | 0,02 | 0,00 | -0,01 | -0,06 | 0,00 | 0,00 | 0,01 | -0,04 | 0,17 | 0,01 | 0,00 | 0,00 | -0,13 | 0,01 | 0,00 | -0,09 | 0,01 | 0,00 | 0,02 | 0,06 | 0,01 | 0,00 | 0,00 | 0,00 | -0,02 |
| f | 0,00 | 0,03 | -0,06 | 0,01 | 0,00 | 0,00 | 0,07 | -0,03 | -0,07 | 0,01 | -0,00 | -0,22 | 0,00 | -0,15 | 0,27 | 0,00 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 | -0,09 | 0,03 | 0,00 | 0,02 | 0,03 | 0,01 | 0,14 | 0,00 | 0,00 | 0,00 |
| g | 0,00 | 0,01 | -0,01 | 0,00 | 0,05 | 0,02 | 0,00 | -0,01 | -0,02 | 0,08 | 0,00 | 0,01 | -0,01 | -0,02 | 0,08 | -0,00 | 0,00 | 0,00 | -0,22 | -0,01 | 0,00 | -0,02 | 0,01 | 0,00 | 0,00 | 0,00 | 0,05 | 0,01 | -0,00 | 0,00 | 0,00 |
| h | 0,01 | -0,11 | 0,00 | 0,00 | -0,02 | 0,08 | 0,09 | 0,00 | -0,01 | 0,00 | 0,00 | -0,02 | 0,00 | -0,00 | 0,05 | 0,00 | 0,00 | 0,00 | -0,05 | 0,00 | 0,00 | -0,05 | 0,17 | 0,00 | 0,00 | -0,02 | -0,19 | 0,06 | 0,00 | 0,00 | 0,00 |
| i | -0,03 | 0,04 | 0,00 | 0,00 | 0,00 | 0,04 | 0,13 | -0,05 | 0,00 | -0,02 | 0,00 | -0,02 | 0,00 | -0,01 | 0,11 | 0,00 | 0,00 | 0,00 | -0,23 | 0,00 | 0,00 | -0,02 | 0,04 | 0,00 | 0,00 | 0,00 | -0,01 | 0,05 | -0,02 | 0,00 | 0,00 |
| j | 0,01 | 0,02 | 0,05 | 0,08 | -0,02 | 0,01 | 0,05 | 0,00 | -0,01 | 0,00 | 0,01 | -0,00 | -0,07 | -0,17 | 0,11 | 0,00 | -0,01 | -0,01 | -0,01 | -0,02 | 0,00 | -0,04 | 0,01 | 0,00 | 0,07 | 0,01 | -0,02 | 0,00 | -0,00 | 0,00 | -0,04 |
| k | -0,01 | 0,01 | -0,02 | 0,00 | 0,00 | -0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,00 | -0,05 | 0,19 | -0,00 | 0,00 | 0,00 | -0,01 | -0,00 | 0,00 | -0,11 | -0,03 | -0,00 | -0,00 | 0,03 | -0,01 | 0,01 | 0,01 | -0,00 | 0,00 |
| l | -0,01 | 0,20 | -0,00 | 0,01 | 0,01 | -0,12 | -0,01 | 0,01 | -0,04 | 0,01 | 0,01 | 0,00 | 0,01 | -0,05 | 0,15 | 0,00 | -0,02 | 0,00 | -0,02 | -0,02 | 0,00 | -0,12 | 0,03 | 0,00 | 0,01 | 0,04 | 0,03 | -0,10 | 0,01 | 0,00 | 0,00 |
| m | 0,02 | 0,01 | 0,01 | 0,04 | 0,04 | 0,00 | 0,01 | 0,00 | 0,00 | 0,04 | 0,01 | 0,00 | 0,00 | -0,05 | 0,24 | 0,00 | 0,00 | 0,00 | -0,00 | 0,01 | 0,00 | -0,50 | -0,05 | 0,00 | 0,03 | 0,15 | 0,00 | -0,00 | 0,00 | 0,00 | -0,01 |
| n | -0,02 | -0,00 | -0,01 | 0,00 | -0,01 | -0,00 | 0,00 | -0,00 | -0,00 | -0,01 | -0,03 | -0,00 | -0,03 | 0,00 | -0,00 | -0,00 | 0,00 | 0,00 | -0,01 | -0,00 | 0,00 | -0,34 | -0,07 | -0,00 | -0,00 | 0,57 | -0,01 | 0,00 | -0,00 | -0,00 | 0,00 |
| o | -0,05 | 0,02 | -0,04 | -0,06 | 0,01 | 0,00 | 0,01 | 0,00 | 0,00 | -0,05 | 0,04 | 0,00 | 0,01 | -0,19 | 0,00 | -0,06 | -0,19 | 0,00 | -0,05 | -0,06 | 0,00 | -0,05 | 0,01 | 0,00 | 0,00 | 0,79 | 0,02 | 0,00 | 0,01 | 0,00 | -0,13 |
| p | 0,00 | -0,00 | 0,04 | -0,13 | 0,00 | 0,00 | -0,00 | 0,00 | 0,00 | 0,02 | 0,03 | 0,00 | -0,00 | -0,00 | 0,01 | 0,00 | 0,00 | -0,10 | 0,00 | -0,53 | 0,52 | -0,00 | 0,00 | -0,01 | 0,03 | 0,01 | 0,00 | 0,00 | 0,00 | 0,12 | 0,00 |
| q | 0,00 | -0,01 | 0,00 | -0,33 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | 0,00 | -0,01 | -0,07 | -0,01 | -0,07 | 0,00 | 0,00 | 0,00 | -0,22 | 0,00 | -0,02 | 0,00 | -0,13 | -0,02 | 0,00 | 1,00 | 0,00 | 0,00 | -0,06 | 0,00 |
| r | 0,00 | 0,00 | -0,01 | -0,07 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | -0,01 | -0,01 | 0,00 | -0,01 | 0,00 | 0,00 | -0,29 | -0,01 | 0,00 | -0,03 | -0,42 | -0,02 | -0,01 | 0,00 | -0,01 | -0,01 | 0,00 | -0,01 | 0,00 | 0,00 | -0,05 | -0,01 |
| s | -0,03 | -0,01 | -0,00 | 0,01 | -0,00 | 0,00 | -0,00 | -0,01 | -0,05 | 0,01 | 0,00 | 0,00 | 0,00 | -0,08 | 0,12 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | -0,03 | 0,01 | 0,00 | 0,02 | 0,04 | 0,01 | 0,00 | -0,03 | 0,00 | 0,00 |
| t | 0,00 | 0,01 | 0,05 | 0,03 | 0,02 | 0,00 | 0,01 | 0,00 | 0,01 | 0,08 | 0,01 | -0,00 | 0,02 | 0,01 | 0,09 | -0,36 | -0,01 | -0,07 | 0,02 | 0,00 | 0,02 | -0,00 | 0,00 | 0,02 | 0,15 | 0,06 | -0,00 | 0,00 | 0,00 | -0,16 | -0,01 |
| u | 0,00 | 0,00 | 0,01 | -0,05 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,01 | 0,01 | 0,00 | -0,05 | 0,00 | 0,01 | 0,84 | 0,00 | -0,19 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,38 | 0,00 | 0,01 | 0,01 | 0,00 | 0,00 | -0,26 | 0,00 |
| v | -0,01 | 0,02 | 0,01 | 0,01 | 0,01 | 0,00 | 0,02 | -0,00 | -0,00 | -0,00 | 0,05 | -0,00 | -0,15 | 0,00 | 0,22 | 0,00 | 0,00 | 0,00 | -0,00 | 0,00 | 0,00 | 0,00 | -0,04 | 0,00 | -0,00 | -0,21 | 0,04 | 0,01 | 0,04 | 0,00 | 0,00 |
| w | -0,01 | 0,21 | 0,00 | 0,00 | 0,01 | 0,02 | 0,03 | 0,02 | 0,01 | 0,01 | -0,01 | 0,00 | -0,02 | -0,17 | 0,16 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | -0,22 | 0,00 | -0,00 | 0,00 | -0,38 | 0,30 | 0,01 | 0,02 | 0,00 | 0,00 |
| x | 0,00 | -0,01 | 0,00 | -0,08 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,09 | -0,03 | 0,29 | 0,06 | -0,17 | -0,01 | 0,00 | -0,10 | -0,08 | 0,00 | 0,00 | 0,00 | -0,04 | 0,27 | -0,01 | 0,00 | 0,00 | -0,13 | -0,01 |
| y | 0,00 | 0,01 | 0,05 | 0,03 | 0,00 | 0,00 | -0,02 | 0,00 | 0,00 | 0,11 | 0,01 | 0,01 | -0,10 | -0,05 | 0,15 | -0,01 | -0,11 | -0,14 | 0,04 | 0,00 | 0,01 | 0,00 | 0,02 | -0,04 | 0,00 | 0,09 | -0,03 | 0,01 | 0,01 | -0,04 | -0,04 |
| z | -0,05 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | -0,00 | -0,00 | 0,00 | 0,00 | 0,01 | 0,00 | -0,08 | -0,06 | 0,73 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,36 | -0,21 | -0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| aa | 0,01 | -0,15 | -0,01 | -0,00 | 0,03 | 0,00 | 0,03 | -0,04 | 0,00 | 0,01 | 0,01 | 0,01 | 0,00 | -0,03 | 0,19 | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | 0,00 | -0,17 | 0,16 | 0,00 | 0,00 | 0,03 | 0,00 | -0,06 | 0,00 | 0,00 | 0,00 |
| ab | 0,00 | 0,00 | -0,02 | 0,00 | 0,00 | 0,30 | 0,01 | 0,03 | -0,02 | 0,00 | -0,02 | -0,01 | 0,00 | 0,00 | 0,10 | 0,00 | 0,00 | 0,00 | 0,03 | 0,00 | 0,00 | -0,12 | 0,06 | 0,00 | 0,00 | 0,03 | -0,38 | 0,00 | 0,00 | 0,00 | 0,00 |
| ac | -0,04 | 0,03 | 0,06 | 0,00 | -0,05 | -0,05 | -0,14 | 0,00 | -0,05 | 0,02 | 0,12 | 0,00 | 0,01 | 0,03 | 0,50 | 0,00 | 0,00 | 0,00 | -0,39 | 0,01 | 0,00 | 0,03 | -0,03 | -0,04 | -0,05 | 0,10 | -0,06 | 0,00 | 0,00 | 0,00 | 0,00 |
| ad | 0,00 | 0,00 | 0,00 | -0,31 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | -0,00 | 0,00 | 0,02 | 0,59 | -0,03 | -0,02 | -0,00 | -0,41 | 0,12 | 0,00 | 0,00 | -0,03 | 0,04 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| ae | -0,02 | -0,02 | -0,02 | -0,02 | -0,02 | 0,00 | 0,00 | 0,00 | 0,00 | -0,12 | 0,00 | 0,00 | -0,08 | -0,20 | 0,00 | -0,04 | -0,06 | -0,04 | -0,04 | -0,18 | 0,00 | -0,08 | -0,02 | 0,00 | 0,00 | -0,06 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |

**Table 16:** The difference between the Markov chain transition matrices created for the nurse's device in the Pori hospital for the periods before and after the system's implementation, on-call time.

| room | a | b | c | d | e | f | g | h | i | j | k | l | m | n | o | p | q | r | s | t | u | v | w | x |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| a | 0,00 | 0,00 | -0,25 | 0,00 | 0,00 | 0,10 | -0,15 | 0,00 | 0,00 | 0,30 | 0,00 | 0,00 | 0,00 | -0,25 | 0,00 | 0,20 | 0,00 | 0,00 | 0,10 | -0,25 | 0,20 | 0,00 | 0,00 | 0,00 |
| b | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | 0,01 | 0,00 | 0,15 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 | 0,00 | -0,23 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,04 | 0,01 |
| c | 0,00 | 0,01 | 0,00 | 0,01 | 0,00 | -0,01 | -0,03 | 0,00 | 0,11 | 0,00 | 0,00 | 0,02 | 0,00 | -0,01 | 0,01 | 0,07 | -0,27 | 0,01 | 0,03 | 0,06 | 0,02 | 0,00 | -0,02 | 0,00 |
| d | 0,00 | 0,00 | 0,00 | 0,00 | 0,08 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,09 | -0,02 | 0,04 | 0,03 | -0,18 | 0,02 | -0,08 | 0,00 | 0,00 | 0,04 | 0,00 | 0,00 | 0,00 |
| e | 0,00 | 0,00 | 0,04 | 0,04 | 0,00 | 0,00 | 0,00 | -0,08 | 0,13 | 0,02 | -0,05 | -0,05 | -0,03 | 0,01 | 0,02 | 0,02 | -0,07 | -0,01 | 0,00 | 0,02 | -0,02 | 0,00 | 0,00 | 0,00 |
| f | 0,02 | 0,02 | -0,06 | -0,05 | 0,02 | 0,00 | 0,09 | 0,00 | 0,03 | -0,01 | 0,00 | 0,02 | 0,00 | 0,02 | 0,00 | 0,02 | -0,09 | -0,05 | 0,00 | 0,04 | 0,00 | 0,02 | -0,05 | 0,00 |
| g | -0,03 | 0,00 | -0,11 | 0,00 | -0,06 | 0,03 | 0,00 | 0,02 | 0,08 | 0,04 | 0,00 | 0,05 | 0,00 | -0,03 | 0,00 | 0,02 | -0,04 | 0,00 | 0,03 | 0,06 | -0,03 | 0,02 | 0,00 | -0,04 |
| h | -0,05 | 0,00 | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | 0,00 | -0,02 | 0,07 | 0,00 | 0,10 | -0,05 | -0,10 | 0,03 | 0,00 | 0,02 | 0,03 | 0,00 | -0,02 | -0,05 | 0,00 | 0,00 | 0,03 |
| i | 0,00 | 0,02 | -0,00 | 0,00 | -0,00 | 0,01 | -0,01 | 0,00 | 0,00 | -0,00 | -0,01 | -0,00 | -0,00 | -0,01 | -0,00 | -0,01 | -0,18 | 0,19 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 |
| j | 0,15 | 0,03 | 0,00 | 0,00 | 0,03 | 0,12 | 0,03 | 0,12 | 0,03 | 0,00 | 0,00 | 0,09 | 0,00 | -0,20 | 0,00 | 0,06 | -0,17 | -0,20 | 0,00 | 0,12 | 0,00 | 0,00 | -0,20 | 0,00 |
| k | 0,00 | 0,00 | -0,02 | -0,02 | -0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,38 | -0,15 | 0,00 | 0,00 | -0,15 | -0,23 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| l | -0,01 | 0,00 | -0,03 | 0,00 | -0,03 | 0,00 | 0,02 | -0,07 | 0,06 | -0,02 | -0,17 | 0,00 | 0,15 | -0,01 | 0,00 | 0,19 | -0,02 | -0,03 | 0,01 | 0,00 | 0,00 | -0,02 | 0,00 | -0,01 |
| m | 0,00 | -0,03 | 0,01 | 0,00 | -0,06 | 0,00 | 0,00 | -0,05 | 0,01 | 0,01 | -0,17 | 0,16 | 0,00 | -0,07 | 0,00 | 0,25 | -0,03 | 0,00 | 0,00 | 0,01 | -0,04 | 0,00 | 0,01 | 0,00 |
| n | 0,00 | 0,00 | -0,06 | 0,01 | -0,13 | 0,00 | 0,00 | 0,00 | 0,31 | 0,00 | 0,00 | 0,00 | 0,06 | 0,00 | 0,00 | -0,08 | -0,05 | -0,19 | 0,00 | 0,03 | 0,09 | -0,06 | 0,00 | 0,06 |
| o | 0,00 | -0,06 | -0,20 | 0,10 | 0,10 | 0,00 | 0,05 | 0,00 | 0,19 | 0,00 | 0,00 | 0,00 | 0,05 | 0,05 | 0,00 | 0,00 | 0,10 | -0,20 | 0,00 | 0,00 | 0,05 | 0,00 | 0,05 | -0,25 |
| p | 0,00 | 0,00 | -0,04 | -0,03 | 0,00 | 0,00 | -0,01 | 0,00 | 0,03 | 0,01 | -0,09 | 0,25 | 0,12 | 0,00 | 0,00 | 0,00 | -0,23 | 0,00 | 0,00 | 0,00 | 0,00 | -0,02 | -0,00 | -0,01 |
| q | 0,00 | -0,02 | -0,09 | -0,01 | -0,02 | -0,01 | -0,02 | -0,00 | 0,29 | 0,00 | -0,07 | 0,05 | 0,04 | -0,01 | 0,00 | -0,10 | 0,00 | 0,01 | 0,01 | -0,01 | 0,00 | -0,00 | -0,03 | -0,02 |
| r | 0,00 | 0,01 | -0,02 | 0,00 | -0,03 | 0,00 | -0,01 | 0,00 | 0,26 | 0,00 | 0,00 | -0,01 | 0,00 | -0,12 | -0,00 | -0,02 | -0,04 | 0,00 | 0,00 | 0,00 | -0,00 | -0,01 | -0,01 | 0,00 |
| s | 0,10 | 0,00 | 0,05 | 0,00 | 0,00 | 0,05 | -0,25 | 0,00 | 0,05 | 0,00 | 0,00 | -0,25 | 0,00 | 0,00 | 0,00 | 0,00 | 0,25 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| t | 0,00 | 0,00 | 0,05 | 0,00 | 0,00 | -0,02 | 0,08 | -0,09 | 0,03 | 0,23 | -0,07 | 0,01 | 0,00 | 0,00 | 0,00 | -0,07 | 0,01 | 0,00 | 0,00 | 0,00 | -0,07 | -0,07 | 0,00 | 0,00 |
| u | 0,02 | 0,02 | 0,06 | 0,04 | -0,10 | -0,04 | -0,04 | 0,00 | 0,12 | 0,04 | -0,04 | 0,00 | -0,05 | 0,10 | 0,02 | 0,00 | -0,03 | -0,07 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,04 |
| v | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,10 | 0,00 | -0,10 | 0,00 | 0,00 | -0,30 | 0,00 | -0,20 | 0,00 | -0,20 | 0,00 | -0,10 | 1,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| w | 0,00 | 0,24 | -0,01 | -0,02 | 0,00 | 0,00 | 0,01 | 0,01 | 0,09 | 0,01 | 0,00 | 0,01 | 0,01 | 0,00 | 0,00 | 0,01 | -0,34 | -0,00 | 0,00 | 0,00 | -0,02 | 0,00 | 0,00 | 0,00 |
| x | -0,07 | 0,14 | 0,07 | 0,00 | 0,00 | 0,00 | -0,07 | 0,00 | 0,14 | 0,00 | 0,00 | 0,00 | 0,00 | 0,07 | 0,00 | 0,00 | -0,38 | 0,14 | 0,00 | -0,13 | 0,00 | 0,00 | 0,07 | 0,00 |

**Table 17:** The difference between the Markov chain transition matrices created for the physician's device in the Rovaniemi hospital for the periods before and after the system's implementation, normal time.

| room | a | b | c | d | e | f | g | h | i | j | k | l | m | n | o | p | q | r | s | t | u | v | w | x |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| a | 0,00 | 0,00 | -0,14 | 0,00 | 0,00 | 0,17 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,17 | 0,00 | 0,00 | 0,00 | 0,17 | -0,14 | 0,00 | -0,29 | -0,14 | 0,00 | -0,14 | 0,17 | 0,17 |
| b | 0,00 | 0,00 | 0,01 | 0,00 | -0,02 | 0,00 | 0,01 | 0,00 | 0,06 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | -0,08 | 0,00 | -0,14 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,18 | 0,00 |
| c | -0,01 | -0,01 | 0,00 | 0,00 | -0,03 | -0,01 | -0,06 | 0,00 | 0,07 | 0,00 | 0,00 | 0,04 | 0,03 | 0,00 | 0,01 | 0,16 | -0,19 | 0,02 | 0,01 | -0,01 | -0,01 | -0,02 | 0,01 | -0,01 |
| d | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 | 0,00 | -0,03 | 0,00 | 0,07 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | 0,08 | 0,04 | -0,17 | 0,09 | 0,00 | 0,00 | -0,04 | 0,00 | -0,06 | 0,04 |
| e | 0,00 | 0,00 | -0,01 | 0,02 | 0,00 | 0,00 | -0,02 | 0,01 | 0,12 | 0,00 | -0,04 | 0,03 | -0,04 | 0,03 | 0,03 | -0,01 | -0,13 | 0,05 | 0,00 | 0,00 | -0,07 | 0,00 | 0,02 | 0,00 |
| f | 0,03 | 0,00 | -0,11 | 0,00 | 0,00 | 0,00 | 0,02 | 0,00 | -0,07 | -0,05 | 0,00 | 0,43 | 0,00 | 0,00 | 0,00 | -0,11 | -0,21 | 0,00 | 0,06 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 |
| g | -0,01 | 0,00 | -0,14 | -0,01 | 0,01 | 0,05 | 0,00 | 0,01 | 0,10 | 0,00 | 0,00 | 0,01 | 0,01 | -0,01 | 0,00 | 0,04 | -0,02 | 0,00 | 0,01 | -0,01 | 0,00 | -0,05 | -0,02 | 0,00 |
| h | 0,00 | 0,00 | 0,00 | 0,00 | -0,07 | 0,00 | 0,00 | 0,00 | -0,03 | -0,14 | 0,00 | 0,38 | -0,12 | 0,00 | 0,00 | 0,01 | -0,12 | 0,00 | 0,00 | 0,05 | 0,03 | 0,00 | 0,00 | 0,01 |
| i | 0,00 | 0,00 | -0,02 | -0,00 | -0,01 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | -0,01 | 0,01 | 0,00 | 0,01 | -0,20 | 0,22 | 0,00 | -0,00 | -0,00 | 0,00 | -0,01 | -0,00 |
| j | 0,00 | 0,00 | 0,00 | 0,00 | -0,10 | -0,01 | 0,00 | 0,07 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,10 | 0,00 | 0,36 | 0,09 | 0,00 | 0,09 | -0,31 | -0,10 | 0,00 | 0,00 | 0,00 |
| k | 0,00 | 0,00 | -0,02 | 0,00 | -0,07 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,23 | -0,21 | 0,00 | 0,00 | -0,08 | -0,38 | -0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| l | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 | 0,02 | -0,01 | 0,08 | 0,06 | -0,01 | -0,10 | 0,00 | 0,04 | -0,00 | 0,00 | 0,00 | -0,04 | 0,01 | 0,00 | -0,00 | -0,02 | 0,00 | 0,00 | 0,00 |
| m | 0,00 | 0,00 | 0,01 | 0,01 | -0,16 | 0,00 | 0,01 | -0,00 | 0,01 | 0,01 | -0,18 | 0,14 | 0,00 | -0,02 | 0,00 | 0,17 | -0,03 | 0,02 | 0,00 | 0,01 | 0,01 | 0,00 | 0,00 | 0,00 |
| n | 0,00 | 0,00 | 0,00 | -0,04 | 0,01 | 0,00 | 0,00 | -0,05 | 0,35 | 0,01 | 0,00 | -0,04 | -0,05 | 0,00 | 0,00 | 0,00 | -0,18 | 0,13 | 0,00 | 0,00 | -0,02 | -0,05 | 0,01 | -0,10 |
| o | 0,00 | -0,31 | 0,05 | 0,00 | -0,03 | 0,00 | 0,05 | 0,00 | 0,15 | 0,00 | 0,00 | -0,08 | 0,05 | 0,00 | 0,00 | 0,00 | 0,15 | 0,05 | 0,00 | 0,00 | 0,10 | 0,00 | -0,21 | 0,02 |
| p | 0,00 | 0,00 | 0,09 | -0,00 | -0,01 | 0,00 | 0,01 | 0,00 | 0,04 | 0,01 | -0,01 | 0,19 | 0,10 | 0,00 | 0,00 | 0,00 | -0,41 | -0,00 | 0,01 | 0,00 | -0,00 | -0,01 | 0,00 | 0,00 |
| q | -0,00 | 0,03 | -0,07 | -0,01 | -0,02 | -0,00 | -0,01 | 0,00 | 0,15 | -0,00 | -0,03 | 0,05 | 0,01 | 0,00 | -0,00 | -0,15 | 0,00 | 0,04 | 0,00 | 0,00 | -0,01 | -0,01 | 0,02 | 0,00 |
| r | 0,00 | -0,01 | -0,01 | -0,00 | -0,01 | 0,00 | -0,01 | -0,00 | 0,08 | 0,00 | 0,00 | -0,01 | 0,00 | 0,01 | 0,00 | -0,00 | -0,03 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | -0,00 | 0,00 |
| s | -0,03 | 0,00 | -0,02 | 0,03 | 0,00 | 0,00 | 0,07 | 0,00 | 0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 | -0,10 | 0,00 | 0,00 | 0,00 | 0,03 | -0,09 | 0,00 | 0,05 |
| t | -0,07 | 0,00 | 0,00 | 0,00 | 0,00 | -0,02 | -0,07 | 0,40 | -0,07 | -0,01 | 0,00 | -0,07 | 0,07 | 0,00 | 0,00 | 0,00 | -0,14 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| u | 0,00 | 0,00 | -0,02 | -0,05 | -0,08 | 0,00 | 0,00 | -0,04 | 0,29 | -0,02 | 0,00 | 0,03 | 0,07 | 0,00 | 0,00 | 0,00 | -0,19 | -0,03 | 0,02 | 0,00 | 0,00 | 0,00 | -0,02 | 0,02 |
| v | 0,00 | 0,00 | -0,29 | 0,00 | 0,00 | 0,00 | -0,33 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,10 | -0,10 | 0,00 | 0,81 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| w | 0,00 | 0,14 | -0,00 | -0,01 | 0,01 | -0,01 | -0,02 | -0,01 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | -0,01 | 0,01 | 0,00 | -0,09 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 |
| x | 0,14 | 0,09 | -0,06 | 0,05 | 0,00 | 0,00 | -0,06 | 0,05 | -0,13 | 0,00 | 0,00 | -0,06 | 0,00 | 0,14 | -0,02 | 0,00 | -0,40 | 0,05 | 0,14 | 0,00 | 0,00 | 0,00 | 0,09 | 0,00 |

**Table 18:** The difference between the Markov chain transition matrices created for the physician's device in the Rovaniemi hospital for the periods before and after the system's implementation, on-call time.

| room | a | b | c | d | e | f | g | h | i | j | k | l | m | n | o | p | q | r | s | t | u | v | w | x |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| a | 0,00 | 0,03 | -0,04 | 0,01 | 0,00 | -0,17 | 0,05 | 0,00 | 0,00 | 0,00 | 0,00 | 0,04 | 0,01 | 0,00 | 0,01 | 0,04 | -0,16 | 0,00 | -0,14 | 0,00 | 0,00 | 0,31 | 0,00 | 0,00 |
| b | 0,00 | 0,00 | -0,03 | 0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,04 | 0,04 | 0,01 | -0,09 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | -0,07 | 0,07 |
| c | 0,00 | 0,01 | 0,00 | 0,00 | -0,00 | 0,00 | -0,18 | -0,00 | 0,00 | 0,00 | -0,01 | 0,01 | 0,00 | 0,00 | 0,00 | -0,06 | 0,21 | 0,00 | 0,01 | -0,01 | 0,00 | 0,01 | -0,00 | -0,00 |
| d | 0,00 | 0,00 | 0,00 | 0,00 | -0,05 | 0,00 | -0,09 | 0,00 | 0,05 | 0,00 | -0,09 | 0,00 | 0,05 | -0,18 | 0,14 | 0,00 | 0,00 | -0,05 | 0,00 | 0,00 | 0,32 | 0,00 | -0,09 | 0,00 |
| e | 0,00 | 0,02 | -0,05 | -0,14 | 0,00 | 0,02 | 0,00 | 0,02 | 0,05 | 0,00 | -0,05 | -0,05 | -0,01 | 0,03 | 0,00 | -0,04 | 0,12 | 0,00 | 0,02 | 0,00 | 0,04 | 0,00 | 0,04 | -0,01 |
| f | -0,03 | 0,03 | 0,04 | 0,00 | 0,00 | 0,00 | 0,07 | -0,13 | 0,03 | -0,03 | 0,00 | -0,03 | 0,00 | 0,00 | 0,00 | -0,06 | 0,01 | 0,00 | 0,03 | -0,13 | 0,03 | 0,13 | 0,03 | 0,00 |
| g | 0,01 | 0,00 | -0,35 | 0,02 | -0,01 | 0,02 | 0,00 | 0,02 | 0,03 | 0,01 | 0,00 | 0,03 | 0,01 | 0,00 | 0,04 | 0,04 | 0,30 | 0,00 | -0,02 | -0,01 | 0,01 | -0,14 | -0,01 | 0,00 |
| h | 0,00 | 0,00 | 0,05 | 0,00 | 0,05 | -0,20 | -0,08 | 0,00 | 0,00 | 0,05 | 0,00 | -0,03 | 0,05 | 0,00 | 0,00 | 0,00 | 0,02 | 0,05 | 0,00 | 0,09 | 0,05 | 0,00 | -0,08 | 0,00 |
| i | 0,00 | 0,00 | 0,00 | 0,01 | -0,00 | -0,01 | -0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | -0,01 | 0,01 | 0,00 | -0,05 | 0,21 | -0,04 | 0,00 | 0,01 | 0,03 | -0,01 | -0,10 | -0,05 |
| j | 0,00 | 0,00 | 0,04 | 0,00 | -0,13 | 0,13 | 0,08 | 0,25 | 0,00 | 0,00 | 0,00 | -0,29 | 0,00 | 0,00 | 0,00 | 0,00 | 0,08 | 0,00 | -0,13 | -0,13 | 0,08 | 0,00 | 0,00 | 0,00 |
| k | 0,00 | 0,00 | -0,08 | 0,00 | -0,05 | 0,00 | 0,00 | 0,00 | -0,08 | 0,00 | 0,00 | -0,25 | -0,05 | -0,03 | 0,00 | -0,08 | -0,38 | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 | 0,00 | 0,00 |
| l | 0,02 | 0,02 | 0,06 | -0,01 | -0,01 | 0,02 | -0,03 | -0,03 | 0,01 | -0,01 | -0,13 | 0,00 | 0,09 | 0,00 | 0,00 | -0,02 | 0,06 | 0,00 | -0,02 | 0,02 | 0,00 | -0,02 | -0,03 | 0,00 |
| m | 0,00 | 0,00 | -0,03 | 0,01 | -0,10 | 0,00 | 0,04 | 0,03 | 0,01 | -0,06 | -0,03 | 0,13 | 0,00 | 0,00 | 0,00 | 0,03 | 0,01 | -0,03 | 0,00 | 0,00 | 0,01 | 0,00 | -0,03 | 0,00 |
| n | 0,00 | 0,08 | 0,05 | -0,01 | -0,20 | 0,00 | 0,03 | 0,00 | -0,03 | -0,06 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 | 0,33 | -0,20 | 0,00 | 0,00 | 0,12 | 0,00 | -0,03 | -0,11 |
| o | 0,00 | -0,19 | -0,09 | 0,00 | 0,03 | 0,00 | 0,13 | 0,00 | -0,13 | 0,03 | 0,00 | -0,13 | 0,00 | 0,09 | 0,00 | 0,06 | 0,06 | 0,03 | 0,06 | 0,00 | 0,03 | 0,00 | -0,09 | 0,09 |
| p | 0,00 | 0,01 | -0,10 | -0,01 | -0,01 | 0,01 | 0,01 | 0,00 | -0,01 | 0,00 | -0,02 | 0,10 | 0,06 | -0,00 | 0,01 | 0,00 | -0,02 | 0,00 | 0,00 | 0,00 | 0,00 | -0,00 | -0,02 | -0,01 |
| q | 0,02 | 0,01 | 0,08 | 0,00 | 0,01 | -0,00 | 0,00 | 0,00 | 0,02 | 0,00 | -0,04 | 0,02 | -0,00 | 0,01 | 0,00 | -0,06 | 0,00 | -0,01 | 0,01 | -0,00 | 0,00 | 0,00 | -0,02 | -0,06 |
| r | 0,00 | 0,08 | -0,00 | 0,12 | -0,00 | 0,00 | 0,00 | 0,08 | -0,06 | 0,00 | 0,00 | 0,00 | 0,00 | -0,04 | 0,00 | 0,00 | -0,16 | 0,00 | 0,00 | -0,04 | 0,00 | 0,00 | 0,04 | 0,00 |
| s | 0,10 | 0,00 | -0,00 | 0,00 | 0,00 | 0,03 | -0,11 | -0,01 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | -0,01 | 0,20 | 0,00 | 0,00 | 0,00 | 0,00 | -0,24 | -0,00 | 0,04 |
| t | 0,00 | 0,00 | -0,20 | 0,00 | 0,00 | 0,07 | 0,00 | -0,10 | 0,00 | 0,13 | 0,00 | -0,30 | 0,00 | 0,00 | 0,00 | 0,00 | 0,50 | 0,00 | 0,00 | 0,00 | -0,10 | 0,00 | 0,00 | 0,00 |
| u | 0,05 | 0,00 | -0,07 | 0,07 | -0,07 | 0,05 | -0,02 | 0,00 | 0,05 | 0,02 | 0,00 | 0,00 | 0,00 | -0,05 | 0,00 | 0,02 | -0,05 | 0,02 | 0,00 | 0,00 | 0,00 | -0,07 | 0,02 | 0,02 |
| v | 0,45 | 0,00 | 0,03 | -0,01 | 0,00 | 0,01 | -0,26 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,05 | 0,08 | 0,01 | -0,19 | -0,01 | 0,01 | 0,00 | -0,04 | -0,03 |
| w | -0,01 | 0,10 | 0,02 | 0,01 | 0,01 | 0,00 | -0,00 | -0,00 | -0,05 | -0,01 | 0,00 | -0,01 | 0,02 | 0,00 | 0,01 | 0,01 | -0,04 | 0,02 | 0,01 | 0,00 | -0,01 | -0,02 | 0,00 | -0,04 |
| x | 0,00 | 0,11 | -0,02 | 0,00 | -0,02 | 0,00 | 0,09 | -0,02 | -0,09 | 0,00 | 0,00 | 0,00 | 0,04 | -0,02 | 0,11 | 0,06 | -0,28 | 0,00 | 0,02 | 0,00 | 0,00 | -0,04 | 0,04 | 0,00 |

**Table 19:** The difference between the Markov chain transition matrices created for the nurse's device in the Rovaniemi hospital for the periods before and after the system's implementation, normal time.

| room | a | b | c | d | e | f | g | h | i | j | k | l | m | n | o | p | q | r | s | t | u | v | w | x |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| a | 0,00 | -0,03 | -0,07 | 0,00 | 0,00 | -0,02 | 0,03 | -0,03 | 0,01 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | 0,01 | 0,03 | -0,02 | 0,00 | -0,01 | 0,00 | 0,00 | 0,04 | 0,01 | 0,01 |
| b | 0,00 | 0,00 | 0,06 | 0,01 | -0,00 | 0,00 | 0,03 | -0,02 | 0,03 | 0,01 | -0,01 | 0,01 | -0,01 | 0,01 | -0,02 | 0,01 | 0,03 | -0,00 | 0,00 | 0,00 | 0,00 | 0,01 | -0,11 | -0,03 |
| c | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | -0,01 | -0,11 | 0,00 | -0,01 | -0,00 | -0,01 | 0,02 | -0,00 | 0,00 | 0,01 | -0,03 | 0,14 | 0,00 | 0,00 | 0,00 | -0,00 | 0,01 | -0,01 | -0,01 |
| d | 0,00 | -0,00 | -0,01 | 0,00 | 0,06 | 0,00 | 0,02 | -0,02 | 0,05 | -0,02 | 0,00 | 0,04 | 0,02 | -0,05 | 0,04 | -0,02 | -0,04 | -0,02 | 0,00 | 0,00 | 0,04 | 0,00 | -0,03 | -0,04 |
| e | 0,00 | 0,00 | -0,00 | -0,04 | 0,00 | 0,00 | 0,03 | 0,00 | 0,04 | -0,01 | -0,04 | -0,01 | 0,03 | 0,02 | 0,01 | -0,03 | 0,09 | -0,04 | -0,01 | 0,00 | 0,00 | 0,00 | -0,03 | -0,00 |
| f | 0,09 | 0,00 | -0,11 | 0,00 | 0,00 | 0,00 | 0,06 | -0,03 | -0,03 | 0,09 | 0,00 | 0,04 | -0,03 | 0,00 | 0,03 | -0,03 | -0,01 | 0,00 | 0,06 | -0,11 | 0,03 | -0,06 | 0,00 | 0,00 |
| g | 0,00 | 0,00 | -0,23 | 0,01 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 | 0,00 | 0,00 | 0,00 | 0,04 | 0,19 | 0,01 | -0,06 | -0,00 | -0,02 | -0,05 | 0,01 | 0,02 |
| h | -0,06 | 0,00 | 0,05 | 0,03 | -0,09 | 0,05 | 0,00 | 0,00 | -0,00 | 0,10 | 0,00 | 0,02 | -0,07 | 0,00 | 0,03 | -0,03 | 0,06 | -0,03 | 0,03 | -0,01 | -0,03 | 0,00 | -0,00 | -0,03 |
| i | 0,00 | -0,01 | -0,02 | 0,00 | 0,02 | -0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | -0,00 | 0,00 | 0,01 | 0,00 | 0,14 | -0,02 | -0,00 | -0,00 | -0,01 | -0,00 | -0,13 | -0,00 |
| j | 0,00 | -0,00 | 0,03 | 0,00 | 0,00 | -0,04 | 0,00 | -0,09 | -0,00 | 0,00 | 0,00 | 0,02 | -0,04 | -0,03 | 0,00 | -0,03 | 0,13 | 0,00 | 0,00 | 0,06 | 0,00 | 0,00 | -0,00 | 0,00 |
| k | 0,00 | 0,00 | -0,09 | 0,00 | -0,02 | -0,01 | 0,00 | 0,00 | -0,03 | -0,01 | 0,00 | -0,15 | -0,16 | 0,00 | 0,00 | -0,14 | -0,38 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | -0,02 | 0,00 |
| l | 0,00 | -0,00 | 0,00 | 0,00 | -0,01 | -0,00 | 0,01 | 0,01 | 0,01 | -0,01 | -0,07 | 0,00 | -0,01 | 0,01 | 0,00 | 0,04 | 0,04 | 0,00 | 0,01 | 0,00 | 0,00 | -0,02 | -0,01 | 0,01 |
| m | 0,01 | 0,00 | -0,02 | 0,01 | 0,01 | 0,00 | 0,01 | -0,01 | -0,02 | -0,03 | -0,16 | 0,02 | 0,00 | 0,00 | 0,01 | 0,09 | 0,11 | -0,01 | 0,00 | 0,01 | -0,01 | -0,01 | -0,01 | 0,00 |
| n | 0,02 | 0,00 | 0,01 | -0,04 | 0,00 | 0,00 | 0,00 | 0,02 | 0,06 | 0,00 | 0,00 | 0,03 | 0,02 | 0,00 | 0,00 | -0,02 | -0,03 | -0,18 | 0,02 | 0,02 | -0,02 | 0,00 | 0,03 | 0,07 |
| o | 0,00 | 0,07 | -0,01 | 0,06 | -0,03 | -0,01 | 0,09 | 0,00 | 0,04 | 0,00 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 | 0,01 | -0,19 | 0,04 | 0,00 | 0,00 | 0,00 | 0,00 | -0,10 | 0,02 |
| p | 0,00 | -0,00 | -0,09 | 0,00 | -0,01 | 0,00 | 0,02 | -0,00 | -0,01 | -0,00 | -0,03 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,12 | 0,01 | -0,00 | -0,00 | -0,00 | -0,00 | -0,01 | -0,00 |
| q | 0,00 | 0,00 | -0,07 | 0,00 | 0,01 | -0,00 | 0,02 | 0,00 | 0,01 | 0,00 | -0,03 | 0,01 | -0,00 | -0,00 | 0,00 | 0,09 | 0,00 | -0,00 | 0,00 | 0,00 | 0,00 | -0,00 | -0,03 | -0,01 |
| r | 0,00 | -0,01 | -0,01 | 0,00 | -0,01 | 0,00 | 0,03 | 0,00 | 0,03 | 0,00 | 0,00 | 0,02 | 0,00 | -0,12 | 0,02 | 0,00 | 0,08 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | -0,02 | -0,03 |
| s | 0,15 | -0,01 | -0,03 | -0,01 | -0,01 | -0,01 | -0,10 | 0,00 | 0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,02 | 0,02 | 0,01 | 0,09 | 0,00 | 0,00 | 0,00 | 0,00 | -0,16 | 0,00 | 0,00 |
| t | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,12 | 0,00 | 0,14 | 0,03 | 0,06 | 0,00 | -0,16 | 0,09 | 0,03 | -0,04 | 0,00 | 0,03 | 0,00 | 0,00 | 0,00 | 0,00 | -0,04 | 0,03 | -0,04 |
| u | 0,00 | 0,00 | -0,03 | 0,02 | 0,02 | 0,00 | -0,14 | -0,02 | 0,09 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,02 | 0,02 | 0,01 | -0,02 | 0,00 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 |
| v | 0,28 | 0,02 | 0,01 | 0,00 | 0,00 | 0,03 | -0,13 | 0,00 | 0,01 | 0,00 | 0,00 | -0,03 | 0,00 | 0,00 | 0,00 | -0,03 | 0,03 | -0,01 | -0,15 | 0,00 | 0,02 | 0,00 | -0,03 | -0,03 |
| w | 0,01 | 0,03 | -0,01 | 0,01 | -0,01 | 0,01 | -0,00 | 0,00 | -0,02 | 0,00 | 0,00 | 0,00 | 0,01 | 0,01 | -0,01 | -0,01 | -0,00 | -0,00 | 0,00 | 0,00 | -0,01 | -0,00 | 0,00 | 0,00 |
| x | 0,00 | 0,02 | -0,03 | 0,00 | 0,02 | 0,00 | 0,05 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,06 | 0,02 | 0,06 | -0,24 | 0,00 | 0,09 | 0,00 | 0,00 | 0,00 | -0,04 | 0,00 |

**Table 20:** The difference between the Markov chain transition matrices created for the nurse's device in the Rovaniemi hospital for the periods before and after the system's implementation, on-call time.

| room | a | b | c | d | e | f | g | h | i | j | k | l | m | n | o | p | q | r | s | t | u | v | w | x | y | z | aa | ab | ac | ad | ae | af | ag | ah | ai | aj | ak | al | am |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| a | 0,00 | -0,00 | 0,05 | 0,05 | -0,04 | 0,00 | 0,00 | 0,01 | 0,00 | -0,08 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,05 | 0,03 | -0,04 | 0,01 | 0,11 | 0,00 | 0,00 | 0,01 | 0,06 | 0,05 | 0,03 | 0,00 | 0,02 | -0,10 | 0,00 | 0,00 | 0,03 | 0,01 | 0,01 | 0,00 | -0,10 | -0,07 | 0,00 |
| b | 0,04 | 0,00 | 0,08 | 0,18 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 | 0,01 | -0,11 | -0,01 | 0,02 | -0,05 | 0,02 | 0,00 | 0,00 | 0,08 | -0,03 | -0,01 | 0,00 | 0,02 | -0,05 | 0,00 | 0,00 | -0,08 | 0,00 | 0,00 | 0,02 | -0,05 | -0,05 | -0,03 |
| c | -0,04 | 0,00 | 0,00 | 0,19 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,01 | -0,16 | 0,02 | 0,00 | 0,03 | 0,00 | 0,00 | 0,00 | 0,01 | -0,01 | 0,00 | 0,00 | -0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | -0,06 | 0,02 | 0,00 |
| d | 0,00 | 0,01 | 0,08 | 0,00 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | -0,07 | -0,01 | -0,01 | 0,00 | 0,00 | -0,01 | 0,00 | -0,01 | -0,14 | -0,01 | 0,02 | 0,02 | 0,00 | -0,01 | -0,01 | 0,00 | 0,02 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,07 | 0,04 | 0,00 |
| e | 0,00 | -0,01 | 0,05 | 0,06 | 0,00 | -0,05 | -0,00 | 0,00 | 0,00 | -0,05 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | -0,01 | 0,07 | -0,17 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,00 | -0,02 | 0,00 | 0,00 | 0,01 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 | 0,02 | 0,14 | -0,05 |
| f | 0,00 | 0,00 | 0,00 | 0,01 | -0,15 | 0,00 | 0,14 | 0,00 | 0,00 | -0,04 | 0,00 | 0,00 | 0,03 | -0,03 | 0,00 | 0,00 | 0,05 | -0,06 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,12 | -0,05 |
| g | 0,00 | 0,00 | 0,02 | -0,04 | 0,06 | 0,05 | 0,00 | 0,05 | 0,00 | 0,00 | 0,00 | 0,02 | 0,17 | -0,04 | 0,03 | 0,02 | -0,29 | -0,05 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 | -0,08 | 0,00 | 0,00 | 0,00 | -0,05 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,13 | 0,00 |
| h | 0,00 | 0,00 | 0,05 | 0,00 | -0,04 | 0,00 | 0,23 | 0,00 | 0,05 | 0,05 | 0,00 | -0,13 | 0,00 | 0,05 | -0,08 | 0,00 | -0,12 | -0,04 | 0,05 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,04 | 0,00 | 0,00 | -0,04 | 0,06 | -0,04 |
| i | 0,00 | 0,00 | 0,17 | 0,00 | 0,00 | 0,00 | 0,00 | 0,17 | 0,00 | 0,00 | 0,00 | 0,17 | 0,17 | 0,00 | 0,00 | 0,00 | 0,17 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,17 | 0,00 | 0,00 | 0,00 |
| j | 0,00 | 0,00 | -0,03 | -0,07 | -0,09 | -0,03 | 0,00 | 0,06 | 0,00 | 0,00 | -0,01 | 0,04 | 0,00 | 0,00 | 0,05 | -0,01 | -0,00 | -0,11 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | -0,03 | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | 0,00 | -0,01 | -0,02 | 0,00 | 0,00 | -0,02 | 0,42 | -0,07 |
| k | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,21 | -0,08 | 0,02 | 0,03 | 0,00 | 0,01 | -0,13 | 0,00 | -0,08 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,07 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,08 | 0,00 |
| l | 0,00 | 0,00 | 0,00 | -0,10 | 0,05 | 0,00 | 0,05 | -0,04 | 0,00 | -0,34 | 0,23 | 0,00 | 0,10 | 0,02 | 0,03 | 0,00 | 0,01 | 0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 | 0,00 | 0,00 | 0,00 | -0,03 | 0,00 | 0,03 | 0,00 | 0,00 | 0,00 | 0,00 | -0,04 | 0,05 | 0,00 |
| m | 0,00 | 0,00 | 0,02 | 0,00 | 0,02 | -0,05 | 0,11 | -0,07 | 0,00 | 0,00 | 0,02 | -0,07 | 0,00 | 0,12 | 0,00 | 0,00 | -0,05 | 0,02 | 0,00 | 0,00 | -0,07 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | -0,05 | 0,02 | 0,00 |
| n | 0,00 | 0,00 | 0,00 | 0,08 | -0,10 | 0,03 | -0,10 | 0,05 | 0,00 | -0,10 | 0,08 | 0,10 | 0,00 | 0,00 | 0,00 | 0,00 | -0,08 | -0,10 | 0,03 | 0,00 | 0,03 | 0,00 | 0,00 | 0,00 | 0,00 | -0,10 | 0,00 | 0,00 | 0,05 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,08 | 0,23 | 0,00 |
| o | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,06 | 0,00 | 0,06 | 0,13 | 0,00 | 0,00 | -0,11 | 0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,06 | -0,02 | 0,00 | 0,00 | 0,00 | 0,00 | -0,65 | 0,00 | 0,06 | 0,39 | -0,02 |
| p | 0,00 | 0,00 | 0,00 | 0,04 | 0,00 | 0,00 | 0,04 | 0,02 | 0,00 | 0,00 | -0,05 | 0,00 | 0,00 | 0,00 | -0,09 | 0,00 | 0,12 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | -0,00 | 0,00 | -0,05 | 0,00 | 0,00 | 0,00 | 0,00 | -0,02 | -0,09 | 0,00 |
| q | 0,00 | -0,00 | 0,00 | 0,09 | 0,03 | 0,00 | 0,00 | -0,02 | 0,00 | -0,03 | -0,00 | 0,00 | 0,00 | 0,01 | -0,03 | 0,04 | 0,00 | -0,15 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | -0,00 | 0,00 | 0,00 | 0,00 | 0,01 | -0,01 | 0,00 | -0,00 | 0,00 | 0,00 | -0,02 | 0,00 | -0,02 | 0,10 | -0,03 |
| r | -0,00 | -0,01 | 0,14 | 0,11 | 0,03 | -0,00 | 0,01 | 0,00 | 0,00 | -0,03 | -0,00 | 0,00 | -0,01 | 0,00 | -0,00 | -0,00 | -0,09 | 0,00 | -0,00 | -0,00 | -0,00 | 0,00 | -0,00 | 0,00 | -0,01 | -0,03 | -0,00 | 0,00 | 0,00 | -0,06 | -0,00 | 0,00 | 0,00 | 0,00 | -0,00 | 0,00 | -0,03 | 0,01 | -0,04 |
| s | -0,02 | 0,03 | 0,06 | -0,08 | 0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 | -0,28 | 0,00 | 0,06 | -0,00 | 0,03 | 0,00 | 0,00 | -0,00 | -0,03 | 0,00 | 0,00 | 0,07 | 0,01 | 0,00 | -0,03 | 0,01 | 0,00 | 0,00 | 0,00 | 0,03 | 0,09 | 0,01 |
| t | 0,01 | 0,00 | 0,03 | 0,04 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,05 | -0,03 | 0,02 | 0,00 | -0,11 | 0,11 | 0,02 | 0,01 | 0,01 | -0,05 | -0,03 | 0,01 | 0,00 | -0,02 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,01 | -0,08 | 0,01 | 0,00 |
| u | -0,00 | -0,02 | 0,01 | 0,08 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | -0,06 | -0,00 | 0,01 | 0,00 | 0,01 | 0,03 | 0,01 | 0,00 | -0,07 | -0,00 | 0,00 | 0,00 | -0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | -0,01 | 0,01 | 0,00 |
| v | 0,01 | 0,00 | 0,00 | -0,06 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 | 0,01 | -0,06 | 0,21 | -0,08 | 0,00 | -0,19 | 0,00 | -0,08 | 0,10 | 0,00 | 0,03 | 0,00 | -0,06 | 0,00 | 0,00 | 0,03 | 0,00 | 0,00 | 0,00 | 0,07 | 0,03 | 0,00 |
| w | 0,00 | 0,01 | 0,00 | 0,05 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | -0,06 | -0,14 | 0,00 | 0,00 | -0,03 | -0,05 | 0,00 | 0,04 | 0,03 | 0,11 | -0,02 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,01 | 0,01 | 0,01 | -0,04 | -0,02 | 0,03 |
| x | 0,00 | 0,00 | 0,05 | -0,07 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,09 | 0,00 | 0,00 | 0,01 | 0,00 | -0,04 | 0,00 | 0,20 | 0,05 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,09 | -0,07 | 0,00 | 0,02 |
| y | 0,05 | -0,01 | 0,00 | 0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,06 | -0,04 | 0,02 | 0,01 | 0,02 | 0,00 | 0,03 | 0,08 | 0,00 | -0,21 | 0,05 | 0,03 | 0,01 | 0,00 | 0,00 | 0,00 | 0,03 | 0,03 | 0,01 | -0,02 | -0,08 | 0,00 | 0,00 |
| z | 0,00 | -0,00 | 0,01 | 0,02 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 | -0,09 | -0,00 | 0,02 | 0,00 | 0,01 | 0,05 | 0,01 | 0,00 | 0,00 | 0,02 | 0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | 0,01 | -0,00 | -0,07 | 0,03 | -0,00 |
| aa | 0,00 | 0,00 | 0,02 | -0,05 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,14 | 0,00 | 0,00 | -0,16 | -0,07 | 0,06 | 0,04 | 0,04 | 0,09 | 0,00 | 0,04 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,08 | 0,02 | 0,04 |
| ab | 0,00 | 0,00 | 0,00 | 0,00 | 0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,21 | 0,12 | 0,08 | 0,00 | 0,00 | 0,00 | -0,17 | 0,04 | 0,00 | 0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,08 | 0,00 |
| ac | 0,04 | 0,00 | 0,00 | 0,09 | 0,06 | 0,00 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | -0,10 | 0,00 | -0,06 | -0,18 | -0,12 | 0,07 | 0,04 | 0,02 | -0,08 | 0,00 | 0,00 | 0,00 | 0,00 | -0,08 | 0,00 | 0,00 | 0,00 | 0,11 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,19 | -0,01 | 0,00 |
| ad | 0,01 | -0,01 | 0,00 | 0,11 | 0,02 | 0,00 | 0,01 | -0,01 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | -0,01 | 0,10 | -0,25 | 0,01 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 | 0,03 | -0,04 |
| ae | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,33 | -0,33 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,33 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 |
| af | 0,00 | 0,00 | -0,20 | 0,00 | -0,20 | 0,00 | 0,08 | 0,00 | 0,00 | 0,00 | 0,00 | 0,17 | 0,17 | 0,08 | 0,08 | 0,00 | -0,32 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,08 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,05 | 0,00 |
| ag | 0,04 | -0,05 | -0,03 | 0,16 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,07 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,14 | 0,02 | 0,00 | 0,07 | -0,17 | 0,02 | 0,07 | 0,00 | -0,05 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,07 | 0,00 | 0,07 | 0,09 | 0,02 | 0,00 |
| ah | 0,03 | 0,03 | 0,09 | 0,00 | -0,18 | 0,00 | 0,00 | 0,00 | 0,00 | -0,18 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,18 | 0,06 | 0,00 | 0,06 | 0,15 | 0,00 | 0,00 | 0,00 | -0,06 | 0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,09 | 0,00 | 0,06 | 0,06 | 0,09 | 0,03 | 0,00 |
| ai | 0,05 | 0,00 | 0,00 | 0,14 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,78 | 0,00 | -0,09 | -0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,02 | 0,17 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,38 | 0,00 | 0,14 | 0,08 | 0,00 | -0,06 |
| aj | 0,00 | -0,03 | 0,00 | 0,06 | -0,13 | -0,02 | 0,00 | 0,00 | 0,00 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | -0,08 | 0,00 | 0,02 | 0,04 | -0,04 | 0,02 | 0,00 | 0,11 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,02 | 0,10 | 0,04 | 0,00 | -0,12 | 0,04 | 0,00 |
| ak | 0,04 | -0,02 | 0,01 | 0,04 | -0,01 | 0,00 | 0,00 | -0,01 | 0,00 | -0,01 | 0,00 | -0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | -0,06 | 0,01 | 0,01 | 0,03 | 0,01 | -0,00 | -0,01 | 0,01 | -0,04 | 0,01 | 0,00 | 0,00 | -0,02 | -0,00 | 0,00 | 0,01 | 0,00 | 0,01 | -0,01 | 0,00 | -0,01 | -0,02 |
| al | 0,01 | -0,01 | 0,02 | 0,07 | 0,06 | 0,01 | 0,01 | -0,01 | 0,00 | -0,02 | 0,01 | 0,01 | 0,01 | 0,01 | 0,00 | -0,02 | -0,05 | -0,13 | 0,00 | 0,01 | 0,00 | 0,01 | 0,00 | -0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,01 | -0,00 | -0,00 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | -0,00 | 0,00 | -0,02 |
| am | 0,00 | 0,00 | 0,00 | 0,00 | -0,15 | -0,03 | 0,00 | 0,00 | 0,00 | -0,09 | 0,00 | 0,00 | 0,00 | -0,01 | -0,01 | 0,00 | -0,19 | -0,28 | -0,01 | 0,00 | 0,09 | 0,09 | 0,09 | 0,00 | 0,17 | 0,08 | 0,09 | 0,09 | 0,09 | 0,12 | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 | 0,00 | -0,04 | -0,07 | 0,00 |

**Table 21:** The difference between the Markov chain transition matrices created for the nurse's device in the Vaasa hospital PO study for the periods before and after the system's implementation, normal time.

| room | a | b | c | d | e | f | g | h | i | j | k | l | m | n | o | p | q | r | s | t | u | v | w | x | y | z | aa | ab | ac | ad | ae | af | ag | ah | ai | aj | ak | al | am |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| a | 0,00 | -0,03 | -0,04 | 0,02 | -0,01 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | -0,10 | -0,01 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | 0,09 | -0,04 | 0,00 | 0,00 | -0,02 | 0,01 | 0,00 | -0,01 | 0,11 | 0,02 | 0,00 | 0,00 | 0,02 | 0,01 | 0,00 |
| b | -0,03 | 0,00 | 0,01 | 0,03 | -0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | -0,01 | 0,00 | -0,01 | 0,01 | 0,03 | 0,03 | -0,01 | 0,01 | 0,00 | -0,01 | -0,00 | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | 0,00 | 0,03 | 0,01 | 0,00 | 0,00 | -0,05 | 0,03 | 0,00 |
| c | -0,02 | 0,01 | 0,00 | 0,16 | -0,00 | -0,00 | -0,00 | 0,00 | 0,00 | -0,01 | 0,00 | -0,01 | 0,00 | 0,00 | -0,00 | 0,01 | -0,01 | -0,10 | -0,01 | -0,00 | -0,01 | -0,00 | 0,00 | -0,01 | 0,01 | -0,03 | 0,00 | -0,00 | -0,01 | -0,02 | 0,00 | -0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,03 | 0,04 | -0,00 |
| d | -0,00 | 0,01 | 0,04 | 0,00 | 0,05 | 0,00 | -0,00 | 0,00 | 0,00 | -0,10 | 0,00 | -0,01 | -0,01 | 0,00 | 0,00 | 0,00 | 0,02 | -0,07 | -0,01 | 0,00 | 0,00 | -0,01 | 0,01 | 0,00 | 0,00 | -0,02 | 0,00 | 0,00 | 0,01 | 0,02 | 0,00 | -0,00 | -0,00 | 0,00 | -0,00 | 0,00 | 0,03 | 0,02 | 0,00 |
| e | 0,00 | 0,00 | 0,00 | 0,03 | 0,00 | 0,15 | 0,01 | -0,00 | 0,00 | -0,01 | -0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,00 | 0,02 | -0,17 | 0,00 | -0,00 | 0,00 | 0,00 | 0,00 | -0,01 | -0,00 | -0,01 | 0,00 | 0,00 | -0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | -0,03 | 0,08 | -0,06 |
| f | 0,00 | -0,01 | 0,02 | 0,01 | 0,06 | 0,00 | -0,03 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | -0,00 | 0,00 | 0,00 | 0,00 | 0,01 | -0,01 | 0,00 | -0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | -0,01 |
| g | 0,00 | 0,00 | 0,03 | 0,10 | 0,14 | -0,13 | 0,00 | -0,00 | 0,00 | 0,00 | 0,01 | 0,03 | -0,00 | -0,03 | -0,03 | 0,03 | 0,06 | -0,17 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 | -0,12 | 0,00 | 0,00 | -0,03 | 0,05 | 0,01 | 0,00 | -0,00 | 0,00 | 0,00 | 0,00 | -0,00 | 0,11 | 0,00 |
| h | 0,00 | 0,00 | 0,03 | 0,03 | -0,03 | 0,00 | 0,15 | 0,00 | 0,06 | -0,03 | -0,03 | -0,04 | -0,04 | -0,03 | -0,03 | 0,00 | 0,03 | -0,13 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,06 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,06 | 0,00 |
| i | 0,00 | 0,00 | -1,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,22 | 0,00 | 0,00 | 0,00 | 0,44 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,22 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,11 | 0,00 |
| j | 0,00 | 0,00 | 0,00 | -0,25 | -0,12 | 0,00 | 0,13 | 0,00 | 0,00 | 0,00 | 0,00 | 0,36 | 0,00 | 0,00 | 0,00 | 0,00 | -0,02 | -0,09 | 0,00 | -0,02 | -0,01 | -0,02 | 0,00 | -0,08 | 0,00 | -0,20 | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | -0,01 | -0,02 | 0,00 | 0,00 | 0,00 | -0,02 | 0,50 | -0,11 |
| k | -0,05 | 0,00 | 0,00 | 0,03 | 0,06 | 0,00 | -0,02 | -0,05 | 0,00 | 0,13 | 0,00 | 0,22 | 0,00 | 0,03 | 0,00 | 0,00 | 0,03 | -0,05 | 0,00 | -0,05 | -0,05 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,05 | -0,07 | 0,00 | -0,04 | 0,00 | 0,00 | 0,00 | 0,00 | -0,05 | 0,01 | 0,00 |
| l | 0,00 | 0,00 | -0,07 | -0,03 | 0,06 | 0,00 | 0,08 | -0,07 | 0,03 | -0,01 | 0,11 | 0,00 | -0,01 | -0,01 | -0,03 | 0,01 | 0,05 | -0,03 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | -0,06 | 0,00 | 0,01 | -0,03 | 0,00 | 0,00 | -0,04 | -0,06 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,03 | 0,11 | 0,00 |
| m | 0,02 | 0,00 | 0,00 | 0,02 | 0,05 | 0,02 | 0,01 | -0,09 | 0,00 | 0,00 | 0,04 | -0,01 | 0,00 | -0,03 | 0,00 | -0,01 | -0,01 | -0,06 | 0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,04 | 0,00 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | 0,05 | -0,13 | 0,00 |
| n | 0,00 | 0,00 | 0,00 | 0,08 | -0,07 | 0,00 | 0,10 | -0,09 | 0,00 | 0,00 | 0,00 | 0,04 | 0,13 | 0,00 | -0,23 | 0,00 | 0,02 | -0,07 | 0,00 | 0,00 | 0,00 | -0,07 | 0,00 | -0,07 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,13 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,13 | 0,23 | 0,00 |
| o | 0,00 | 0,00 | 0,00 | 0,00 | 0,05 | 0,06 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,05 | 0,00 | -0,01 | -0,07 | 0,10 | -0,01 | 0,00 | 0,00 | 0,00 | 0,06 | -0,01 | -0,01 | -0,01 | 0,00 | 0,00 | 0,06 | 0,11 | 0,00 | 0,00 | 0,00 | -0,03 | -0,74 | 0,00 | 0,05 | 0,34 | 0,00 |
| p | -0,04 | 0,00 | -0,03 | 0,02 | -0,04 | 0,00 | 0,03 | 0,00 | 0,00 | 0,00 | 0,02 | 0,03 | 0,02 | 0,00 | 0,00 | 0,00 | 0,18 | -0,08 | 0,00 | 0,03 | 0,00 | 0,02 | 0,00 | 0,00 | 0,01 | -0,04 | 0,00 | 0,00 | 0,00 | 0,05 | 0,00 | -0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,05 | -0,19 | 0,00 |
| q | -0,01 | -0,00 | -0,02 | 0,08 | 0,11 | 0,01 | 0,00 | -0,01 | 0,00 | -0,01 | 0,00 | -0,01 | 0,01 | 0,00 | -0,09 | 0,03 | 0,00 | -0,12 | 0,00 | 0,00 | 0,01 | -0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | -0,00 | -0,00 | 0,00 | -0,00 | -0,01 | -0,00 | -0,04 | 0,00 | -0,00 | 0,10 | -0,02 |
| r | -0,01 | 0,00 | 0,02 | 0,08 | 0,06 | 0,00 | -0,00 | -0,00 | 0,00 | -0,01 | -0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,02 | -0,00 | -0,00 | 0,01 | 0,00 | -0,00 | -0,00 | -0,03 | 0,00 | 0,00 | -0,01 | -0,06 | 0,00 | -0,00 | -0,01 | -0,00 | 0,00 | 0,00 | -0,01 | 0,03 | -0,04 |
| s | 0,02 | 0,01 | -0,01 | 0,04 | -0,05 | 0,01 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,02 | 0,01 | 0,00 | 0,03 | -0,17 | 0,00 | 0,02 | 0,01 | 0,03 | 0,03 | -0,02 | 0,02 | 0,07 | 0,01 | -0,03 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,04 | 0,02 | 0,00 |
| t | -0,01 | 0,00 | 0,01 | 0,02 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | -0,02 | -0,00 | 0,00 | 0,02 | 0,10 | 0,01 | -0,00 | -0,01 | -0,06 | -0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | -0,08 | 0,05 | 0,00 |
| u | 0,00 | 0,01 | 0,01 | 0,01 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | -0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,00 | -0,02 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | -0,05 | 0,01 | 0,00 | 0,00 | -0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | -0,00 | 0,00 | -0,00 | -0,00 |
| v | 0,00 | 0,02 | -0,01 | 0,03 | 0,02 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | -0,01 | 0,01 | 0,01 | 0,05 | 0,01 | 0,00 | 0,00 | -0,02 | 0,00 | -0,09 | 0,01 | -0,01 | 0,01 | 0,01 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | -0,03 | 0,02 | -0,01 |
| w | -0,02 | -0,01 | 0,01 | 0,01 | -0,01 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | -0,01 | 0,01 | -0,00 | 0,00 | -0,02 | -0,04 | -0,00 | 0,00 | -0,03 | 0,01 | 0,04 | 0,04 | 0,01 | 0,00 | -0,01 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,05 | 0,01 | -0,02 |
| x | 0,00 | 0,00 | -0,00 | -0,01 | -0,02 | 0,00 | 0,00 | 0,00 | 0,00 | -0,08 | 0,00 | -0,02 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | -0,01 | -0,03 | -0,00 | 0,02 | 0,00 | -0,00 | 0,00 | 0,04 | 0,09 | 0,06 | 0,02 | 0,00 | -0,01 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | -0,01 | 0,02 | 0,01 | -0,06 |
| y | 0,05 | 0,01 | 0,02 | 0,02 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | -0,01 | 0,02 | -0,02 | -0,02 | -0,00 | 0,04 | 0,02 | 0,00 | -0,02 | -0,01 | 0,00 | -0,00 | -0,01 | 0,00 | 0,00 | -0,00 | -0,01 | 0,00 | -0,00 | -0,03 | -0,02 | -0,01 |
| z | -0,01 | -0,00 | 0,00 | 0,00 | -0,00 | -0,00 | -0,00 | -0,00 | 0,00 | -0,02 | -0,00 | 0,00 | 0,00 | 0,00 | -0,00 | 0,00 | -0,01 | -0,03 | 0,00 | 0,01 | -0,01 | 0,04 | 0,06 | -0,00 | -0,01 | 0,00 | -0,00 | 0,00 | -0,00 | -0,00 | 0,00 | -0,00 | 0,01 | 0,00 | -0,00 | 0,00 | -0,02 | 0,00 | -0,01 |
| aa | -0,00 | 0,00 | 0,00 | 0,00 | 0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,01 | 0,01 | -0,01 | -0,04 | 0,02 | 0,12 | -0,00 | 0,01 | -0,11 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | 0,01 | 0,00 | -0,02 | 0,02 | -0,00 |
| ab | 0,00 | 0,00 | -0,03 | 0,03 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,06 | 0,04 | 0,01 | 0,03 | 0,03 | 0,06 | -0,11 | -0,02 | 0,00 | 0,00 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,06 | 0,01 | -0,03 |
| ac | -0,04 | 0,00 | 0,00 | 0,11 | -0,04 | -0,02 | -0,02 | 0,00 | 0,00 | 0,00 | 0,00 | -0,02 | 0,00 | -0,02 | 0,00 | 0,02 | -0,03 | -0,17 | 0,09 | 0,00 | -0,04 | 0,06 | -0,02 | 0,00 | 0,02 | 0,05 | 0,00 | 0,02 | 0,00 | -0,05 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,11 | 0,05 | -0,04 |
| ad | 0,00 | -0,00 | -0,01 | 0,08 | 0,06 | -0,01 | -0,00 | -0,00 | 0,00 | -0,01 | 0,00 | -0,01 | 0,00 | 0,00 | -0,00 | 0,01 | 0,05 | -0,31 | 0,02 | 0,01 | 0,01 | 0,01 | 0,01 | -0,00 | -0,00 | 0,07 | -0,00 | 0,01 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | -0,00 | 0,00 | 0,02 | 0,03 | -0,03 |
| ae | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,13 | -0,38 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,63 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,13 | 0,00 |
| af | -0,04 | 0,00 | -0,08 | -0,08 | 0,03 | 0,00 | 0,00 | 0,07 | 0,00 | 0,00 | 0,12 | 0,28 | 0,16 | 0,00 | -0,08 | 0,00 | 0,00 | -0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,20 | -0,08 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,05 | 0,00 |
| ag | 0,01 | 0,03 | 0,03 | 0,03 | 0,03 | 0,01 | -0,01 | 0,00 | 0,00 | -0,02 | 0,00 | -0,01 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | -0,04 | 0,00 | -0,04 | 0,03 | -0,00 | 0,05 | 0,00 | -0,08 | 0,01 | -0,01 | -0,01 | 0,00 | -0,02 | 0,00 | 0,00 | 0,00 | -0,01 | -0,01 | -0,02 | 0,06 | 0,03 | -0,01 |
| ah | -0,04 | 0,05 | 0,11 | 0,05 | -0,05 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,48 | 0,00 | 0,00 | -0,05 | 0,00 | 0,00 | 0,21 | 0,00 | 0,00 | 0,00 | 0,06 | 0,01 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,16 | -0,14 | 0,11 | 0,01 | 0,00 |
| ai | 0,00 | 0,00 | 0,00 | 0,14 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,84 | 0,00 | -0,09 | 0,00 | 0,00 | 0,00 | 0,13 | 0,00 | 0,00 | -0,01 | -0,01 | 0,14 | 0,00 | 0,00 | 0,00 | -0,01 | 0,00 | 0,00 | -0,01 | 0,27 | 0,00 | 0,00 | 0,14 | 0,00 | 0,14 |
| aj | 0,00 | 0,04 | -0,03 | 0,00 | -0,17 | 0,00 | 0,00 | 0,00 | 0,00 | -0,03 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | -0,17 | 0,00 | 0,04 | -0,03 | 0,00 | 0,00 | 0,00 | 0,09 | 0,04 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,00 | 0,23 | 0,12 | 0,00 | 0,00 | -0,09 | 0,00 | -0,03 |
| ak | 0,01 | 0,02 | 0,03 | 0,06 | 0,01 | 0,01 | 0,00 | -0,00 | 0,00 | -0,00 | -0,00 | 0,00 | 0,01 | -0,00 | 0,00 | 0,00 | 0,01 | -0,09 | 0,00 | -0,00 | -0,01 | -0,00 | 0,01 | 0,00 | 0,00 | -0,06 | 0,00 | -0,00 | -0,00 | -0,01 | 0,00 | -0,00 | -0,00 | -0,00 | -0,00 | -0,01 | 0,00 | 0,02 | -0,00 |
| al | 0,01 | -0,01 | 0,02 | 0,05 | 0,13 | 0,01 | 0,01 | -0,02 | 0,00 | 0,00 | -0,01 | 0,02 | 0,00 | -0,00 | 0,01 | -0,00 | -0,06 | -0,14 | 0,00 | 0,02 | -0,01 | -0,00 | -0,00 | 0,00 | -0,00 | -0,01 | 0,00 | 0,00 | 0,00 | -0,00 | -0,01 | -0,00 | 0,01 | 0,00 | 0,00 | 0,00 | 0,01 | 0,00 | -0,01 |
| am | 0,00 | -0,01 | -0,01 | 0,00 | -0,24 | -0,02 | 0,00 | 0,00 | 0,00 | -0,11 | 0,00 | -0,01 | 0,00 | 0,00 | -0,01 | 0,00 | -0,02 | -0,18 | 0,00 | 0,00 | 0,00 | -0,01 | 0,07 | -0,03 | -0,02 | 0,49 | 0,08 | 0,00 | -0,01 | 0,01 | 0,00 | 0,00 | 0,05 | 0,00 | -0,01 | 0,00 | -0,02 | 0,02 | 0,00 |

**Table 22:** The difference between the Markov chain transition matrices created for the nurse's device in the Vaasa hospital PO study for the periods before and after the system's implementation, on-call time.